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TEMPORAL SAMPLING REQUIREMENTS FOR ESTIMATING THE MEAN NOISE LEVEL IN THE VICINITY OF MILITARY INSTALLATIONS

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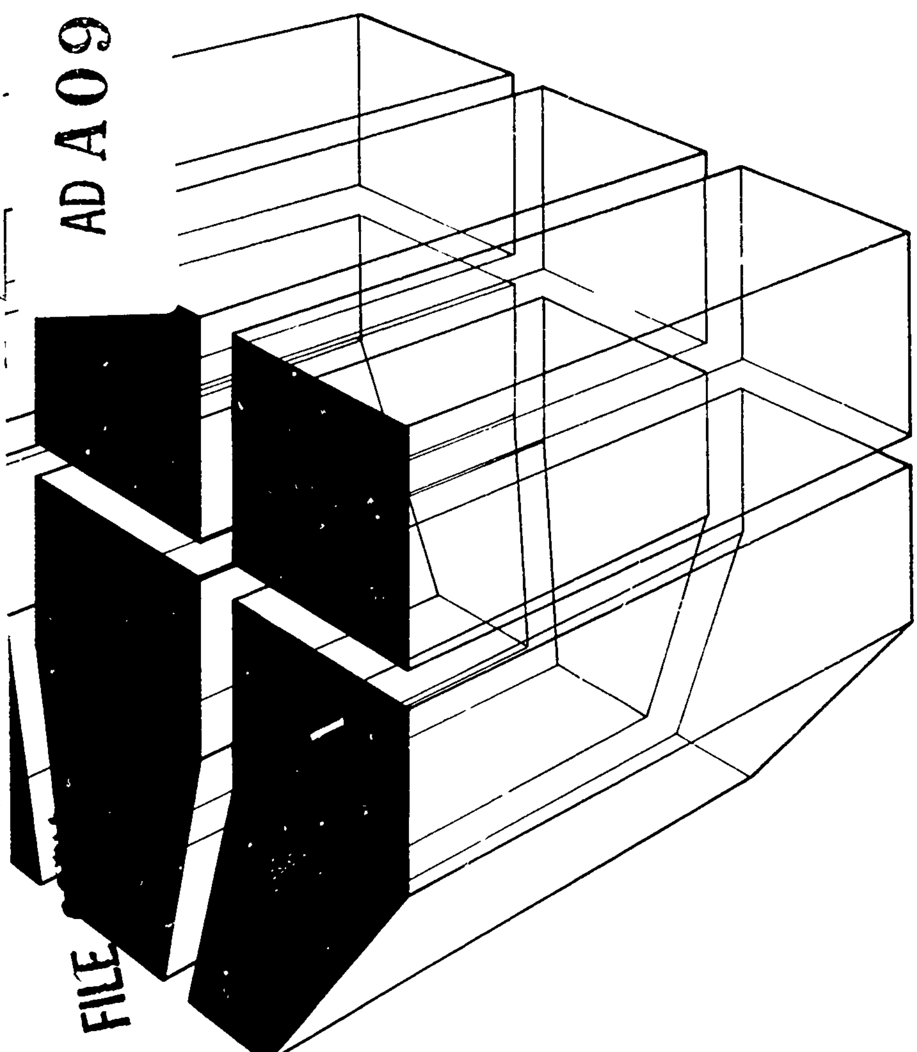

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High sound exposure levels in the vicinity of military installations are an increasingly important acoustics problem, especially with the recent emphasis on the establishment of environmental standards. This research addresses the problem of using monitored data to establish estimates of long-term average noise levels which can be determined with prespecified levels of precision and statistical significance. Daily average noise-level data exhibit chara[illegible]istics amenable to time series modeling. The Dynamic

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Data System (DDS) method is used to characterize noise data by autoregressive-moving average (ARMA) models for the purpose of determining the variance of the sample mean of such data so that sampling requirements can be derived. Daily average noise data from Los Angeles International, Boston Logan, Washington Dulles, and Washington National airports are analyzed to (1) ascertain the effects of operations, weather, and nonairport (community) noise on measured sound exposure levels and (2) derive associated sampling requirements for the estimation of the sample mean noise levels. General results indicate that 30 to 60 days of consecutive sampling are required to estimate the mean noise level with a precision of ±50 percent of the sample mean at the 0.05 level of significance. To assess sampling requirements at Fort Bragg, a combined multiplicative operations and weather model is developed. Noise data based on artillery blast operations were predicated via a computer model for average weather conditions. A model which represents the day-to-day effects of weather or operations data is proposed and used with the computer-generated data based on operations to develop the combined models. This model predicts sampling requirements of at least 50 to 150 consecutive days of sampling at Fort Bragg.

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FOREWORD

This research was conducted for the Directorate of Military Programs, Office of the Chief of Engineers, under Project 4A762720A896, "Environmental Quality Technology," Task A, "Environmental Impact Monitoring Management Assessment and Planning," Work Unit 024, "Validation and Refinement of Community Response to Blast Noise Contours." The applicable QCR is 3.01.007. Mr. Gordon Velasco, DAEN-MPE-I, was the OCE Technical Monitor.

The work was performed by the Environmental Division (EN) of the U.S. Army Construction Engineering Research Laboratory (CERL) and William A. Kline and Richard E. DeVor of the Department of Mechanical and Industrial Engineering of the University of Illinois at Urbana-Champaign. Dr. R. K. Jain is Chief of CERL-EN.

COL Louis J. Circeo is Commander and Director of CERL and Dr. L. R. Shaffer is Technical Director.

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1 INTRODUCTION

Background

High sound exposure levels in the immediate proximity of airports and military installations are an increasingly important acoustics problem. Recent environmental standards have emphasized the significance of improved equipment design, better operations planning, and new techniques for noise abatement.[1] The measurement of noise levels in the vicinity of Army installations and the associated statistical assessment of the precision of mean-level estimates is an important element of the overall problem.

While it is possible to continuously monitor the daily average sound exposure level, it is economically desirable to sample for a relatively short period of time and use this information to draw reliable inference about the long-term (yearly) mean level. Until recently, techniques for assessing environmental noise specified sampling over extremely short periods of time, e.g., from a few minutes to perhaps a single day.[2] However, the time varying nature of noise data when viewed as a time series (hourly or daily averages) suggests that short-term sampling may lead to serious inaccuracies in the estimation of a long-term (yearly) average noise level. For example, the 24-hr periodic pattern in hourly average sound level may vary from about 40 to 85 decibels (dB). Daily averages commonly vary from 50 to 80 dB. These wide ranges for sound level, together with the fact that the data generally exhibit high positive autocorrelation and high coefficients of variation, suggest that small and/or short sampling periods may provide both imprecise and inaccurate mean value estimates.

The techniques of time series modeling in general and that of Dynamic Data System (DDS) in particular provide a powerful methodology for an assessment of mean level estimation precision and the formulation

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[1]Quiet Communities Act of 1978, PL 95-609.

[2]D. C. Pies and L. C. Sutherland, Evaluation of Spatial Sampling Techniques for Community Noise Surveys, Report No. WR-77-5 (Wyle Research Laboratory, 1977); and J. Stearns, L. C. Sutherland, and D. C. Pies, Community Noise Monitoring--A Manual for Implementation, Report No. WR-76-8 (Wyle Research Laboratory, 1976).

of sampling strategies.[3] The autocorrelated nature of the data, particularly the degree of positive correlation between neighboring observations, generally increases the amount of consecutive sampling required over sampling where independence can be assumed. In this study, the DDS method is used to model many noise time series to quantitatively characterize the autocorrelation in the data toward the specification of sampling requirements and the formulation of efficient sampling strategies.

Objective

The objective of this study is to develop models which can assess the requirements for sampling noise levels in the vicinity of large distributed noise sources such as airports (in general) and Army installations (in particular) for the purpose of obtaining reliable estimates of long-term mean noise levels.

Approach

This study was designed to develop a model which predicts sampling requirements to obtain data for the reliable estimation of the long-term average noise levels in the vicinity of Army installations. Daily average noise levels at a particular site, when examined over many consecutive days (e.g., 6 to 12 months) show a characteristic behavior of a stationary stochastic process with significant levels of positive autocorrelation. When sampling over a number of consecutive days to obtain data for the estimation of the long-term mean level, both the overall level of variation (coefficient of variation) and the degree of autocorrelation (correlation factor) impact the precision associated with the mean-level estimate. These two factors must be quantified to define rigorous sampling requirements.

The analysis of time series by the method of DDS provides a powerful methodology for the quantification of autocorrelation. Thus, the estimation of the variation in sample means is estimated from a sequence of autocorrelated data. Time series of consecutive daily average monitored noise levels were modeled by autoregressive-moving average stochastic models and the parameters of these models were used to assess the precision associated with mean-level estimates.

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[3] R. E. DeVor, P. D. Schomer, W. A. Kline, and R. D. Neathammer, "Development of Temporal Sampling Strategies for Monitoring Noise," Journal of the Acoustical Society of America, Vol 66, No. 3 (September 1979), pp 763-771; and R. E. DeVor, W. A. Kline, and K. M. Tingley, "Analysis of Environmental Noise Data by the Method of Dynamic Data System," Proceedings of the 10th Modeling and Simulation Conference (April 1979), pp 419-428.

This study analyzed a large quantity of monitored noise data from two sources: (1) a military installation--Fort Bragg, and (2) four large commercial airports--Los Angeles International, Boston Logan, Washington Dulles, and Washington National. The analysis of the airport data was used to: (1) evaluate the utility of the DDS modeling approach and to establish the methodology for the derivation of sampling requirements, and (2) develop a model to describe the effects of weather or daily measured sound levels. This latter purpose was particularly significant, since it led to the postulation of a weather model, i.e., a time series model which indicates the stochastic effect of weather on noise from a fairly constant source.

The noise data for Fort Bragg were based on a computer program which predicts noise as a function of the frequency and intensity of military operations.[4] Because these data were free from the effects of weather, and because weather effects had to be considered in order to avoid biasing operations data (which might lead to an overestimation of sampling requirements), a weather/operations model was developed. This model extrapolated weather effects from the data collected during the airport analyses; the result was a multiplicative model which combined an airport-derived weather model and a computer-generated operational blast noise model. The autocorrelated function of this multiplicative was derived and used to calculate sampling requirements to achieve a prespecified level of precision in the estimate of the long-term mean noise level.

Mode of Technology Transfer

The results of this study will impact on the Army Regulation Series 200, Environmental Quality.

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[4] V. Pawlowska and L. Little, The Blast Noise Prediction Program: User Reference Manual, Technical Report N-75/ADA074050 (U.S. Army Construction Engineering Research Laboratory [CERL], August 1979).

2 DYNAMIC DATA SYSTEM (DDS) MODELING

The Mean Level Inference Problem

At the outset of this study, it was proposed to formulate a strategy for sampling the noise level signal at a given location and use the data obtained to estimate the *yearly* average noise level with some prespecified level of precision. While this information may be quite useful from an environmental impact point of view, it will be both insightful and necessary to carefully examine the time-varying nature of the signal over the entire year. This will not only impact the estimation and inference problem, but strongly influence the practical interpretation given to an average or mean-level estimate.

Mathematical Statement of the Problem

Consider a finite set of discrete measurements, $X_1, X_2, \ldots, X_N$, obtained by uniformly sampling a continuous signal X_t at equispaced intervals Δt. Assume that:

1. The sample interval size Δt is a prespecified constant and is of a size sufficient to capture the structure of the continuous signal.

2. X_i need not be Gaussian, but $\{X_t\}$ should constitute a <u>stationary</u> time series; i.e., fluctuate about a fixed mean with a constant level of irregularity.

3. The length of record $N\Delta t$ is sufficient to adequately encompass the significant long-term features of the continuous signal.

If a series of observations $X_1, X_2, \ldots, X_N$ is used to estimate the average yearly noise level, the specific nature of the autocorrelation in the data that will impact the estimate of the true mean level is given by

$$\mathrm{Var}(\overline{X}) = \frac{1}{N}\left[\gamma_0 + 2\sum_{k=0}^{N-1}\left(1 - \frac{|k|}{N}\gamma_k\right)\right], \qquad \text{[Eq 1]}$$

where

$\gamma_0 = \mathrm{Var}(X_t)$

k = time lag

N = sample size

γ_k = kth lag autocovariance between X_t and X_{t+k}

For a stationary time series, the $\{\gamma_k\}$ converge to zero as k increases so that for large N, Eq 1 reduces to the approximation:

$$\mathrm{Var}\ (\overline{X}) \approx \frac{1}{N} \sum_{-\infty}^{\infty} \gamma_k . \qquad \text{[Eq 2]}$$

If the data are autocorrelated, then Eq 1 may be rewritten as

$$\mathrm{Var}\ (\overline{X}) = (\gamma_0/N)C, \qquad \text{[Eq 3]}$$

where:

C is a factor which varies with and accounts for the autocorrelated nature of the data.

In general, for positively autocorrelated data, the autocorrelation factor C will be greater than 1; for negatively autocorrelated data, it will be between 0.0 and 1.0. This phenomenon can be appreciated intuitively by examining Figure 1. It is clear that for positively autocorrelated data, excursions or runs above and below the mean will produce sample averages with wider dispersion about the true mean than would be produced if the data were random. Similarly, negatively correlated data are characterized by successive high and low values which tend to "average" to values quite closely clustered about the true mean. These characteristic behaviors may be quantified by the autocorrelation factor, which for the modeling technique used in this report can be shown to be solely a function of the parameters of an autoregressive-moving average (ARMA) model for the data.

If the data are uncorrelated, then $\gamma_k = 0$ for $k \geq 1$ and

$$\mathrm{Var}\ (\overline{X}) = \gamma_0/N . \qquad \text{[Eq 4]}$$

Therefore, a $(1-\alpha)$ 100 percent confidence interval for $\bar{X}$ will be given by

$$\overline{X} \pm z_{1-\alpha/2}\ [\mathrm{Var}(\overline{X})]^{1/2} \qquad \text{[Eq 5]}$$

where α is the level of significance. Strictly speaking, the t distribution should be used instead of the unit normal z distribution to account for the uncertainty in estimating the variance of the sample mean. However, for the sample sizes encountered in this report, the t distribution is closely approximated by the z distribution. The problem to be

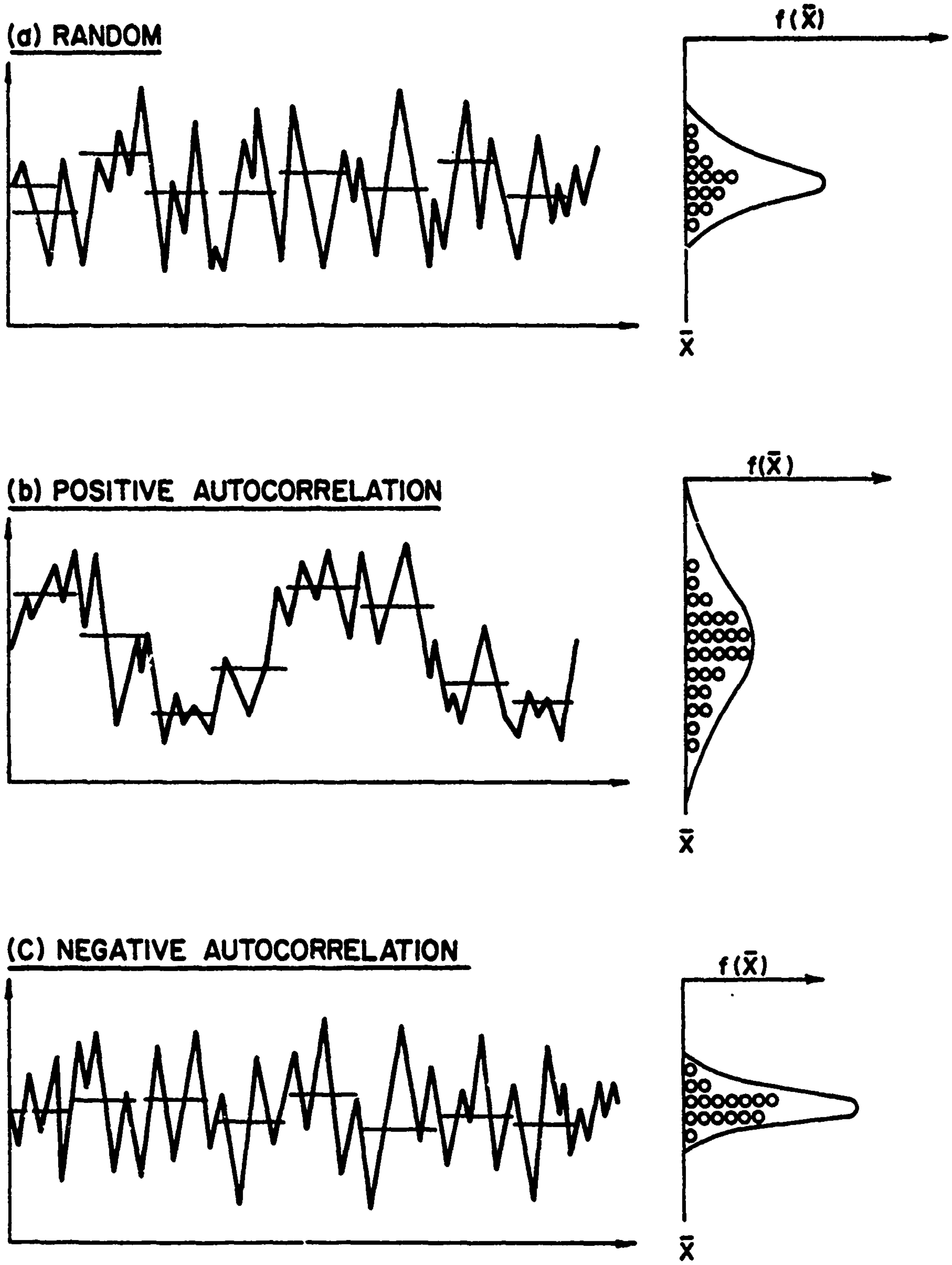

Figure 1. Autocorrelated structures in time series and their impact on sample mean precision.

addressed is, then, to determine the precision with which the sample mean $\bar{X}$ based on N observations estimates the true mean level, or alternatively, to specify the length of record (number of observations) needed to estimate the true mean μ by $\bar{X}$ within a certain prespecified interval at a given level of statistical significance.

The autocovariance function, $\{\gamma_k\}$, plays a central role in these calculations. This study was concerned with the use of parametric stochastic models of the ARMA class for the estimation of the $\{\gamma_k\}$. This approach provides a mathematically appealing approach to the problem.

Time Series Modeling by DDS

The DDS Modeling Approach

In recent years, modeling stochastic phenomena by the general class of ARMA models has found a tremendous growth in applications in the area of forecasting and control. Several unified strategies have been proposed to facilitate this modeling with varying philosophies on the model building procedure, physical interpretation of models, and the manner in which both deterministic and stochastic trends are modeled. The DDS methodology has particular appeal for several reasons which go beyond the scope of this report. In particular, the modeling and interpretation of physical systems is greatly enhanced by this approach.

When only stochastic variation is evident in the data (no deterministic trends such as periodicities), the general class of ARMA models given in Eq 6 is used for modeling.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_n X_{t-n} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_m a_{t-m}, \quad \text{[Eq 6]}$$

where X_t is the observation in the time series at time t

a_t is the random shock at time t; a_t is normally and independently distributed, $NID(o,\alpha^2)$

ϕ_i is the ith autoregressive parameter

θ_i is the ith moving average parameter

n is the number of autoregressive parameters

m is the number of moving average parameters.

In the DDS modeling methodology, m is generally defined to be n-1, although the final appropriate fitted model may have m < (n-1). The poles, λ_i, of the model are defined as the roots of the autoregressive portion of the model:

$$(Z^n - \phi_1 Z^{n-1} - \ldots - \phi_n) = \prod_{i=1}^{n} (Z-\lambda_i) \qquad \text{[Eq 7]}$$

where λ_i is the ith pole

Z is the transform operator such that $Z^{-1}X_t = X_{t-1}$.

It can be shown by using the elementary theory of linear operators on Hilbert space that any stationary stochastic system can be approximated by an autoregressive moving average model of order (n, n-1).

For the use and interpretation of the ARMA (n, n-1) model class, it is useful to consider two important characterizations of the model: (1) Green's function, and (2) the autocovariance function. Green's function, G_k, can be expressed as a sum of weighted exponential functions:

$$G_k = g_1(\lambda_1)^k + g_2(\lambda_2)^k + \ldots\ldots + g_n(\lambda_n)^k \qquad \text{[Eq 8]}$$

where λ_i is the ith pole

g_i is the ith Green's function coefficient.

The Green's function coefficients are the residues of H(z)/z, where H(z) is the z transform of Eq 6.

$$H(z) = \frac{Z^{n-m}(Z^m - \theta_1 Z^{m-1} - \ldots. - \theta_m)}{(Z^n - \phi_1 Z^{n-1} - \ldots\ldots - \phi_n)} \qquad \text{[Eq 9]}$$

Thus the Green's function coefficients are computed by Eq 10:

$$g_i = \left[(Z-\lambda_i)H(Z)/Z\right]\Big|_{Z=\lambda_i} \quad i = 1,2,\ldots n \qquad \text{[Eq 10]}$$

According to the Wold decomposition, X_t may be expressed as a sum of orthogonal vectors $G_j a_{t-j}$, in an infinite dimensional space. That is:

$$X_t = \sum_{j=0}^{\infty} G_j a_{t-j} \qquad \text{[Eq 11]}$$

For stable systems, only a relatively few number of vectors need to be added to obtain X_t. Physically, the Green's function may be thought of as describing the nature of the dynamic response of the system to a random disturbance a_t, i.e., the impulse response.

The autocovariance function of the general ARMA (n,m) model may be derived from Eq 11 by noting that the kth autocovariance γ_k is given by

$$\gamma_k = E(X_t \cdot X_{t+k}) \qquad \text{[Eq 12]}$$

where E denotes expected value.

Similar to Green's function, the autocovariance function can be expressed as a sum of weighted exponential functions:

$$\gamma_k = d_1(\lambda_1)^k + d_2(\lambda_2)^k + \ldots + d_n(\lambda_n)^k \qquad \text{[Eq 13]}$$

where d_i is the ith autocovariance coefficient

$$d_i = \sigma_a^2 \sum_{j=1}^{n} \frac{g_i g_j}{1-\lambda_i \lambda_j} \qquad i=1,2,\ldots,n$$

The fact that Green's function and the autocovariance function can be expressed solely in terms of the model parameters ϕ, θ, and σ_a^2 is found to be most useful later when an estimate of the variance of the sample mean is to be obtained given an appropriate ARMA model for the data.

In the DDS methodology, the appropriate model for a given set of data is determined by successively fitting models of progressively higher order by the method of least squares until a satisfactory fit is obtained. Analysis of variance is performed for each model, and the F test is used to determine when the reduction in the residual sum of squares from one model to the next is statistically significant. A Q-test is performed on the sample autocorrelations of each fitted model to determine if significant correlation remains in the a_t series. Initially, an ARMA (2,1) model is fit to the data.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-1} + a_t - \theta_1 a_{t-1} \qquad \text{[Eq 14]}$$

Models of the form ARMA(4,3), ARMA(6,5),...., ARMA(2n,2n-1) are then successively fit. The model is incremented by steps of two--i.e., ARMA(2n,2n-1)--so that the roots of the model can be either real or complex at any time, thereby not forcing a real root to be present in a model for a process which does not physically have that characteristic. Modeling is terminated when the F test fails to show significance when the next higher-order model is fit. Individual model parameters near zero may be examined for significance by computing their (1-α) 100 percent confidence intervals. Insignificant parameters are dropped and the remaining parameters are re-estimated. In general, an ARMA(n,m) model results.

Estimation of the $\{\gamma_k\}$ *From the ARMA Model Parameters*

By using the ARMA model class to characterize a time series of noise data, the $\{\gamma_k\}$ for these data [and in Eq 2] can be estimated by functions of the model parameters alone. In particular,

$$\mathrm{Var}\,(\bar{X}) = \frac{\sigma_a^2}{N}\left[\frac{\left(1 - \sum_{j=1}^{m} \theta_j\right)}{\left(1 - \sum_{i=1}^{n} \phi_i\right)}\right] = \frac{1}{N}\left[\sum_{i=1}^{n} d_i + 2\sum_{i=1}^{n} \frac{d_i\lambda_i}{1-\lambda_i}\right] \qquad \text{[Eq 15]}$$

The variance of the disturbances σ_a^2 may be calculated by recursively calculating the a_t from the fitted model and then substituting into Eq 16:

$$\hat{\sigma}_a^2 = \frac{\sum_{i=1}^{N} (\hat{a}_i)^2}{N - (n + m + 1)} . \qquad \text{[Eq 16]}$$

The approach to assessing the confidence associated with the sample mean $\bar{X}$ of the autocorrelated sequence $X_1, X_2, \ldots X_N$ is then as follows:

1. The DDS modeling methodology is used to find the appropriate ARMA(n,m) model for the data by successive fitting. Since, in general, the models are nonlinear in the parameters, an iterative nonlinear least squares routine is required to estimate the parameters.

2. Based on the fitted model and estimated parameters $\hat{\phi}$, $\hat{\theta}$, and $\hat{\sigma}_a^2$; the variance of the sample mean from Eqs 15 and 16 is estimated.

3. A (1-α) 100 percent confidence interval for the true mean μ from Eq 5 is established.

It should be noted that in all of the modeling of noise data which follows, the data are modeled and precision estimates in the sample mean are determined in units of sound exposure or mean-square pressure. Confidence intervals determined in mean-square pressure are then transformed to sound exposure level (SEL) in decibels by the transformation,

$$SE_{dB} = 10 \log_{10} (\text{mean-square pressure}). \qquad \text{[Eq 17]}$$

Analysis of Noise Data

This section uses two sets of noise data to illustrate the modeling technique and its use in the mean-level estimate precision assessment problem. One is derived from a site in the vicinity of Naval Air Station (NAS) Miramar, San Diego, CA (site 30 in Figure 2); the second was taken from nearby Lindbergh Field (Site 50 in Figure 2), the commercial San Diego Airport. Both sets of data were recorded between January and June of 1976. Figure 2 is a map of NAS Miramar and shows the locations of several monitoring sites around the airfield. Figures 3 and 4 show the data in units proportional to mean-square pressure. Each data point is a time-weighted 24-hr average noise level, referred to as the Community Noise Equivalent Level (CNEL). CNEL values are determined from the equation

$$\text{CNEL} = 10 \log \frac{1}{P_o^2 T} \left[\int_0^{25\ 200} 10P_a^2(t)dt + \int_{25\ 200}^{79\ 200} P_a^2(t)dt + \int_{79\ 200}^{86\ 400} 10P_a^2(t)dt \right], \qquad \text{[Eq 18]}$$

where P_0 = 20 micropascal

T = 86400 sec.

DDS Modeling

The DDS modeling methodology was applied to each data set to obtain an adequate ARMA(n,m) model. For the NAS Miramar data, successive fitting and testing for adequacy via the F test revealed that an ARMA(8,7) model is required to describe the data. For the Lindbergh Field data, an ARMA(2,1) model was found to provide an adequate representation.

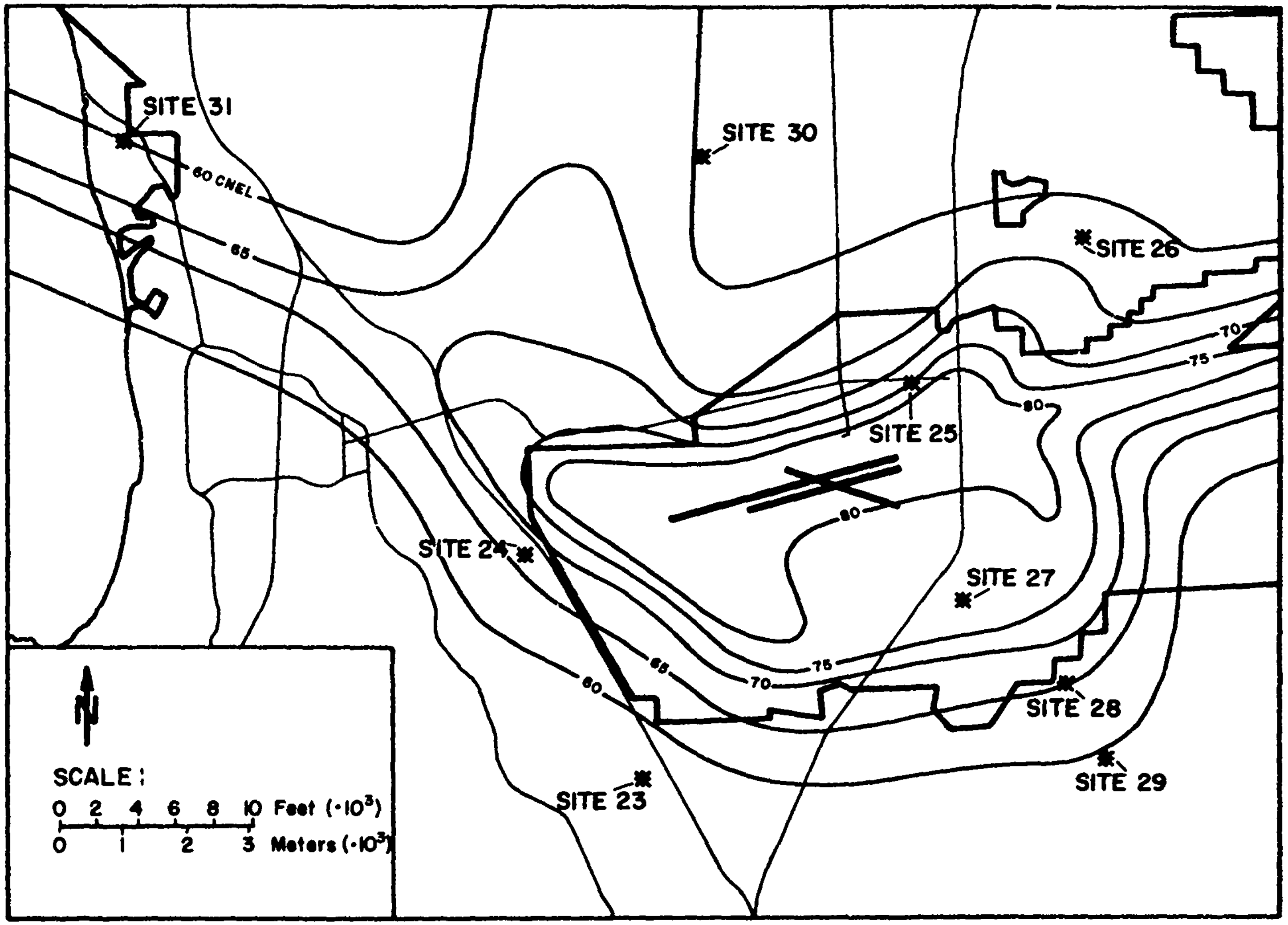

Figure 2. Map of monitoring sites at NAS Miramar.

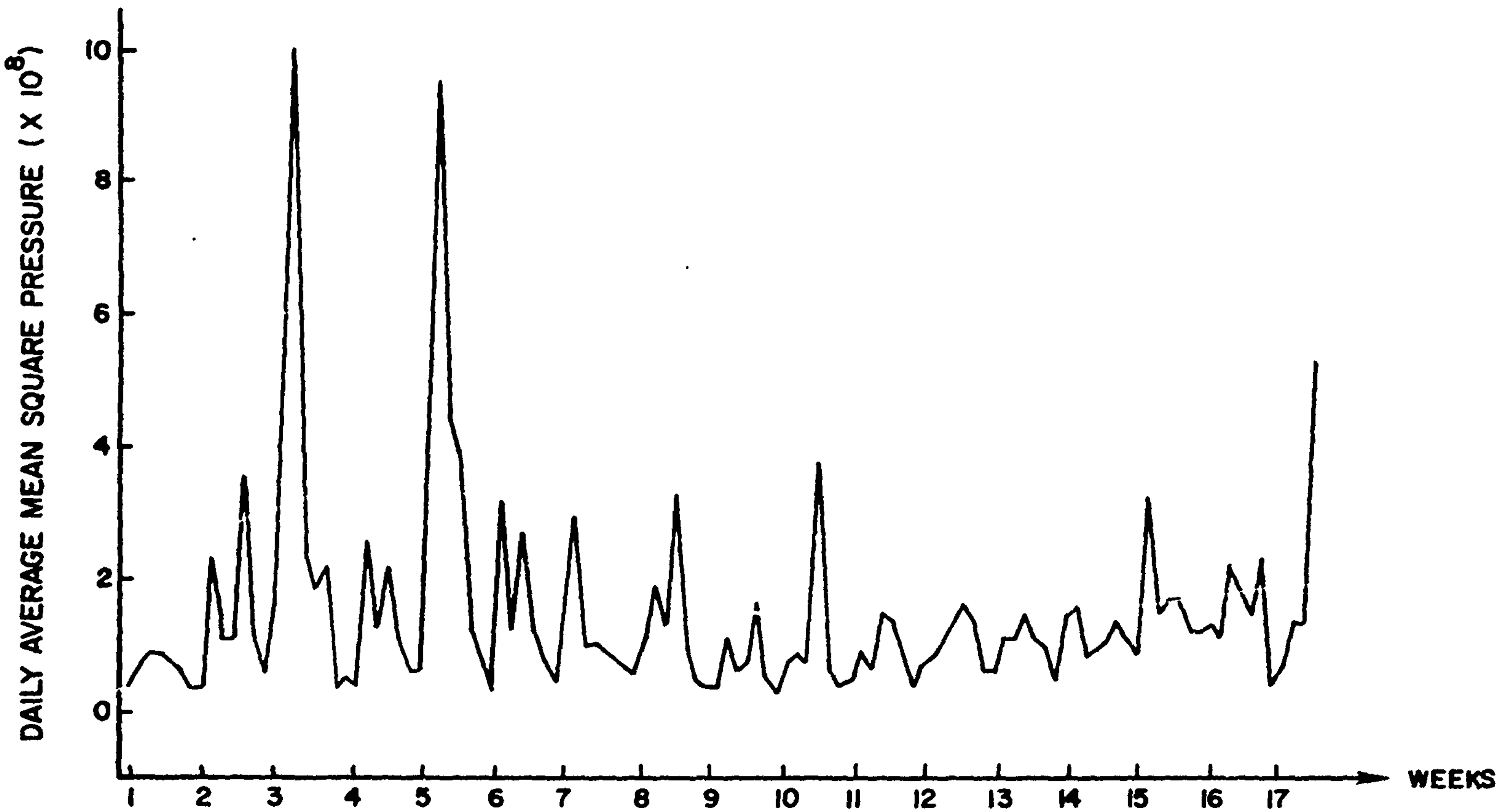

Figure 3. NAS Miramar -- data from Site 30.

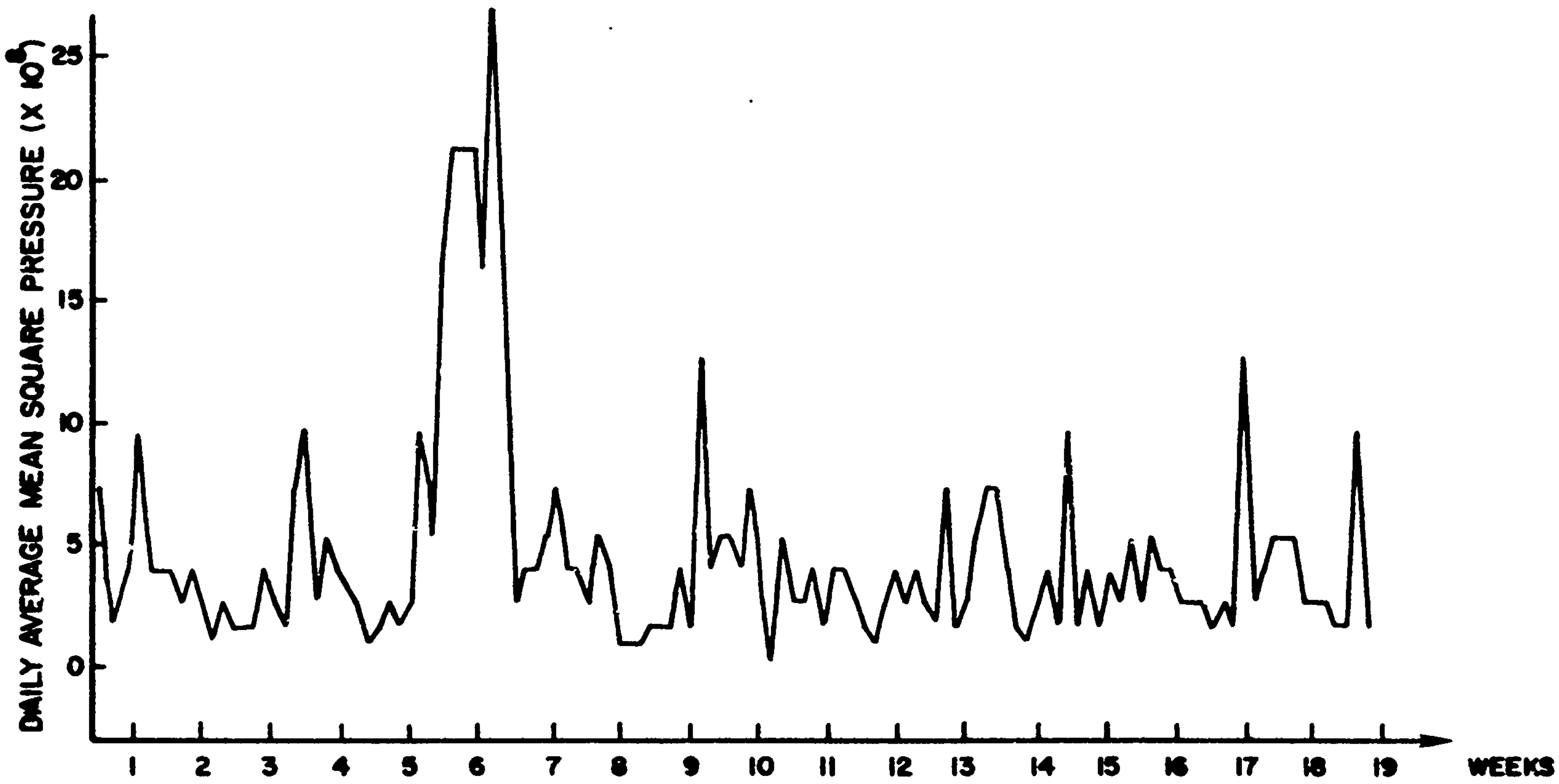

Figure 4. Lindbergh Field -- data from Site W50.

Table 1 lists the fitted models and the statistical parameter estimates for both Site 30 and Site W50 data. As can be seen from the table, the two noise-level time series appear to vary considerably in terms of both their average levels and stochastic structure. For Site 30, the mean level is equivalent to 61.4 dB, while for Site W50 it is considerably higher--76.0 dB. The differences in the autocorrelated structure will be more fully revealed when an assessment in the precision of the sample mean $\overline{X}$ is made.

Mean-Level Precision Assessment

To assess the precision of the estimate of the sample mean, a $(1-\alpha)$ 100 percent confidence interval for the true mean μ may be determined. For the Site 30 data, using Eq 15 and σ_a^2 from Table 1:

$$\mathrm{Var}(\overline{X}) = 4.80 \times 10^{10}$$

A 95 percent confidence interval for μ is then given by Eq 5:

$$1.69 \times 10^{6} \pm 4.29 \times 10^{5}$$

In decibel units, the mean estimate is 62.3 dB and the 95 percent confidence interval is bounded by 61.0 and 63.3 dB. The interpretation of this interval is that one is 95 percent confident that the true mean for these data is estimated within about ± 25 percent in mean-square pressure, which is about -1.3, +1.0 dB.

It is interesting to compare the result above to the parallel result obtained if it is assumed that the daily average noise levels ordered in time are independent. In this case, using Eq 3:

$$\mathrm{Var}(\overline{X}) = 2.419 \times 10^{10}$$

A 95 percent confidence interval is given by Eq 5:

$$1.69 \times 10^{6} \pm 0.30 \times 10^{6},$$

which says that the mean can be estimated within ± 18 percent in units of mean-square pressure. Hence, by neglecting the effect of autocorrelation in the data, the impression is given that for a fixed sample of data (here, approximately one-third of a year), the mean can be estimated more precisely than is really possible.

Table 1

Fitted Models and Parameter Estimates for the CNEL Mean Square Pressure Data for Sites 30 and W50

Site	Fitted ARMA(n,m) model	$\overline{X}$	$\hat{\gamma}_o$	$\hat{\sigma}_a^2$
NAS Miramar (Site 30)	$X_t = 0.616X_{t-1} - 0.330X_{t-2} + 0.159X_{t-3}$ $+ 0.118X_{t-4} - 0.132X_{t-5} + 0.065X_{t-6}$ $-0.156X_{t-7} - 0.011X_{t-8} + a_t + 0.563a_{t-1}$ $-0.528a_{t-2} + 0.046a_{t-3} + 0.483a_{t-4}$ $-0.149a_{t-5} + 0.137a_{t-6} - 0.693a_{t-7}$	1.69×10^6	2.54×10^{12}	1.75×10^{12}
Lindbergh Field (Site W50)	$X_t = 0.633X_{t-1} + 0.135X_{t-2}$ $+ a_t + 0.202a_{t-1}$	51.9×10^6	1186.57×10^{12}	750.21×10^{12}

When analyzing the Lindbergh Field data (Site W50), the effect of autocorrelation is even more pronounced (Figure 4). Accounting for the autocorrelated nature of the data using Eq 3:

$$\mathrm{Var}(\overline{X}) = 4876 \times 10^{10}.$$

Assuming independence using Eq 4:

$$\mathrm{Var}(\overline{X}) = 652.1 \times 10^{10}.$$

The corresponding 95 percent confidence intervals are given by

1. Assuming the data are autocorrelated (Eq 5):

   $$51.9 \times 10^{6} \pm 6.98 \times 10^{6}.$$

2. Assuming the data are independent (Eq 5):

   $$51.9 \times 10^{6} \pm 2.60 \times 10^{6}.$$

In other words, while an uncorrelated analysis would suggest a mean-level estimate within ± 5 percent based on the 182 data points, the autocorrelated analysis shows that our precision is really only ± 13.4 percent.

Summary of Modeling Results and Sample Size Requirements

In addition to the two sites analyzed above, data were obtained from Sites 23 and 31 in the area of NAS Miramar. For one of these additional sites (Site 31), two time series of CNEL measurements were formed over different time periods to examine the stationarity and homogeneity of the data over an extended period of time. (Figure 2 shows CNEL contours.)

Figures 5 and 6 show portions of the data analyzed for Sites 23 and 31. Visual inspection of these two noise time series seems to indicate a marked difference in the time-varying nature of the data. The data for Site 23 seem much more random than those at Site 31, which appears to have more of a positive correlation pattern (almost a weekly pattern) with two large "spikes" around the fourth and sixth weeks.

Modeling by DDS showed that for the Site 31 data (both noise time series) an ARMA(4,3) model appeared to adequately describe the autocorrelated structure of the data. For Site 23, autocorrelated structure of any significance only seemed to appear at lags 7 and 14 (weekly periodic-type structure). A model of the following form was fit to these data:

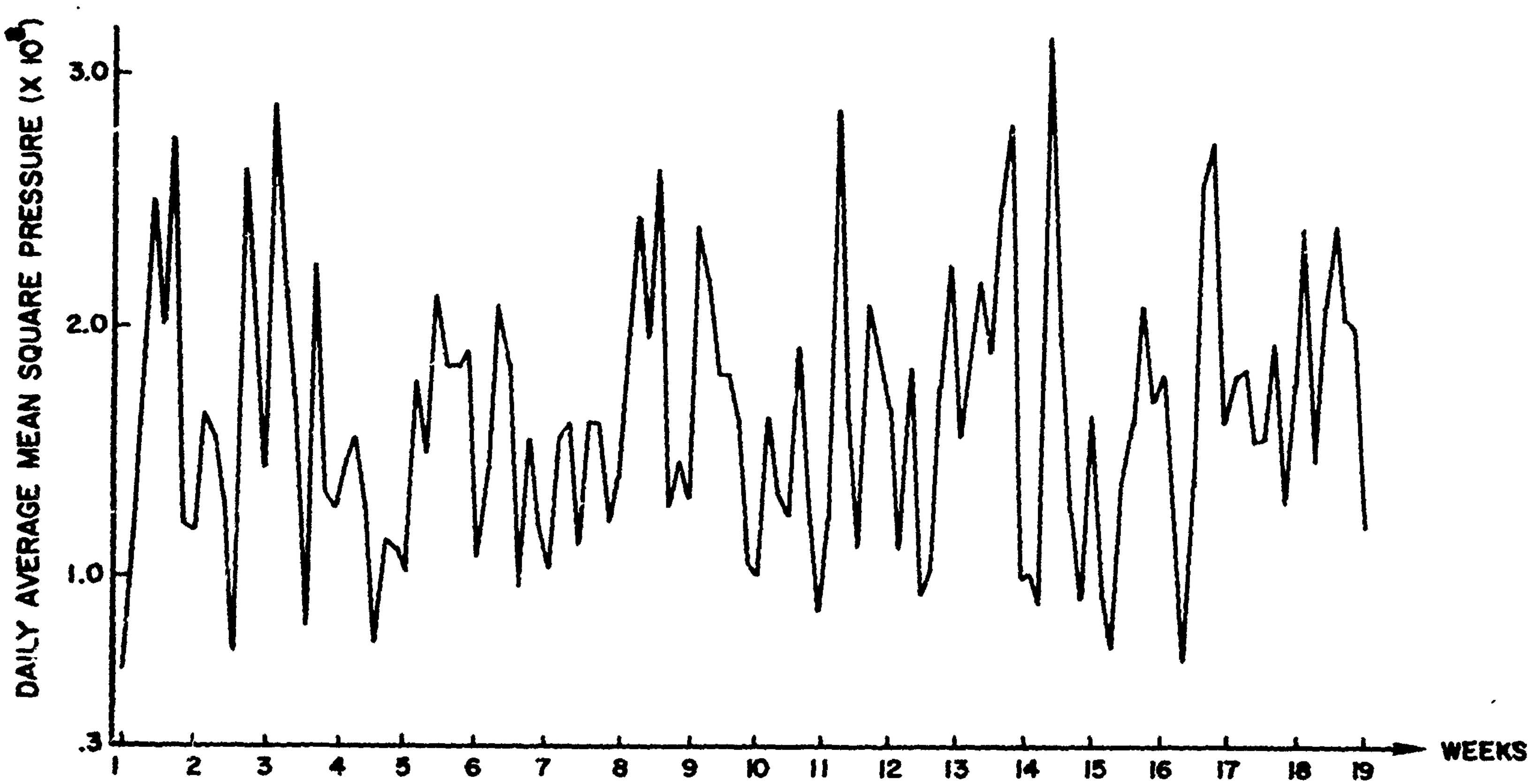

Figure 5. NAS Miramar -- data from Site 23.

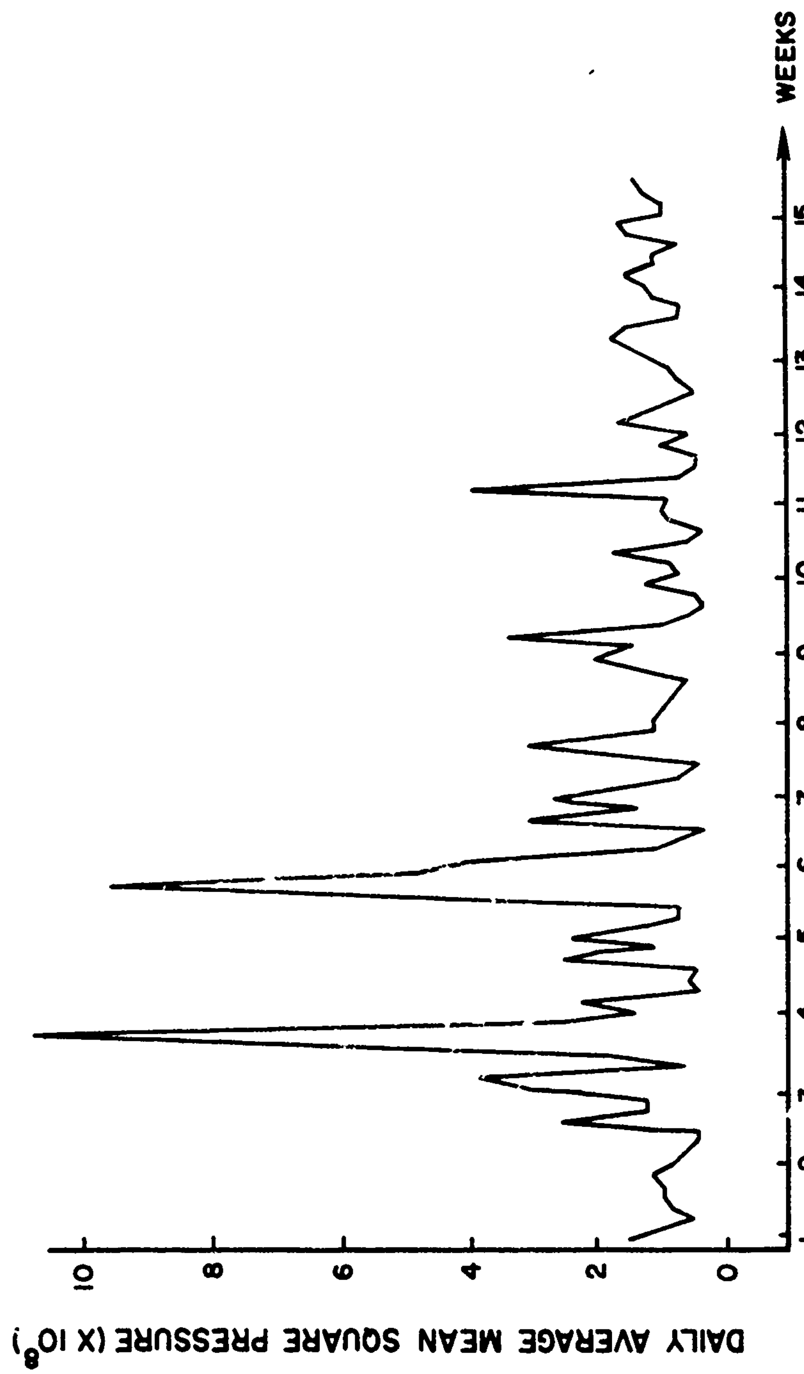

Figure 6. NAS Miramar -- data from Site 31.

$$X_t = -0.667X_{t-7} - 0.315X_{t-14} + a_t + 0.355a_{t-1} \quad \text{[Eq 19]}$$

When the parameters of the above fitted model are used to determine the variance estimate of the sample mean, an interesting result is obtained. Contrary to the results from all other sites, the use of Eq 19 Var($\overline{X}$) vs the independence assumption (Eq 4) shows that smaller sample sizes are required when autocorrelation is recognized than when independence is assumed. In summary, using Eqs 15 and 4, respectively:

$$\text{Var}(\overline{X}) = 10.4 \times 10^{12} \text{ (autocorrelated)},$$

$$\text{Var}(\overline{X}) = 24.4 \times 10^{12} \text{ (independence)}.$$

This suggests that these data are dominated by negative correlation. This explains the somewhat oscillatory appearance of the data in Figure 5. Note also that the general variance of these data (γ_0) is quite small relative to the data from the other sites (0.31×10^{12} vs 2.33 and 2.73×10^{12} for Sites 30 and 31, respectively). Hence, it is not surprising that the sample size requirements for mean-level precision assessment at Site 23 are quite low. In fact, for a ±50 percent precision in the mean-level estimate (in units of mean-square pressure), only one daily average is required (two daily averages if autocorrelation is neglected). To obtain a ±25 percent precision, only three daily readings are required (seven daily readings if autocorrelation is neglected).

Table 2 summarizes the modeling and sampling strategy analysis for all of the sites evaluated. It is interesting to observe the wide variation in the autocorrelated nature of the data from these four sites and its concomitant impact on the sample size requirements. For example:

1. Sites 30 and 31 (Figures 3 and 6) are typified by data which have two structural components visible in the time series: (a) irregular runs of an average length of about 7 days, and (b) a few very sharp spikes indicating that high mean-square pressure levels occur somewhat infrequently over an extended period of time. Table 2 indicates that the time series modeling approach responded to these data characteristics by conveying a general positive correlation content which produced sample size requirements in excess of those required under the assumption of no correlation in the data. Sample size requirements are about 100 percent greater than would be called for assuming independence of the data.

2. For Site W50 (Lindbergh Field), Figure 4 shows the same general patterns as Sites 30 and 31, except that the irregular runs (above and below the mean) seem longer. This suggests even stronger positive correlation. The DDS model for this site confirms this general appearance by

Table 2

Summary of Sample Size Requirements

							±50% of $\overline{X}$ precision	
Site	Model	$\overline{X}$ (10^6)	$\hat{\gamma}_0$ (10^{12})	$\hat{\sigma}_a^2$ (10^{12})	Number of data points	$Var(\overline{X})$ Eq 16 (10^{10})	Sample size required (autocorrelated)	Sample size required (independence)
23	See Eq 19	1.69	0.308	0.28	126	0.104	1 (3, ±25%)	2 (7, ±25%)
30	ARMA(8,7)	1.84	2.535	1.75	105	4.80	23	12
31	ARMA(4,3)	1.58	2.332	1.80	140	4.58	33	15
31A	ARMA(4,3)	1.63	2.734	1.92	107	5.23	33	16
W50	ARMA(2,1)	51.9	1186.57	750.21	182	4264.15	50	7

producing very high sample size requirements relative to the assumption of independence (50 days vs 7 days).

3. For Site 23 (Figure 5) the data are quite uniform in variation level (no large spikes) and have much more of an oscillatory pattern as opposed to a pattern of longer, irregular runs. The DDS model conveys this mathematically by producing a sample size requirement which is: (a) much lower than for the other sites, and (b) such that actually fewer samples are required, relative to assuming independence.

3 ANALYSIS OF AIRPORT DATA

Los Angeles International (LAX)

Continuous daily monitored CNEL values were supplied by LAX for the period from May 1, 1977 to December 31, 1977 for the 12 monitoring locations shown in Figure 7. These daily data were converted to values proportional to daily sound exposure (SE) by dividing each daily CNEL value by 10 and raising that result to the 10th power:

$$SE = 10^{(CNEL/10)} \qquad \text{[Eq 20]}$$

The resulting noise series plots for the 12 sites by day after transforming the data as described in Eq 19 are shown in Appendix A. Note that SE values are used to estimate the yearly mean day/night average sound level (DNL) or CNEL value, which by definition is calculated from the yearly mean SE.

Using the DDS method, ARMA models were developed for 15 of the 16 time series. One of the LAX time series (Site I-1 in Appendix A) was found to contain strong deterministic trends and, thus, was not modeled using the DDS stochastic models. Using the method described in Chapter 2, the estimated parameters of the fitted ARMA models were used to determine the correlation factors for each of the time series and thereafter estimate the variance of the sample means. Table 3 summarizes the model type and autocorrelation factor for each of the time series modeled. This table also contains the mean and variance for the original noise time series. To aid in interpretation, the coefficient of variation which is the ratio of the standard deviation to the mean (of the original noise series) is also included.

Based on the assumption of independence of the data (no autocorrelation on a day-to-day basis), the number of samples required to estimate the long-term (yearly) mean for any desired level of precision can be calculated. In this report, an estimation precision of ±50 percent of the mean with a 95 percent confidence level has been chosen. It must be noted that a ±50 percent band in the estimation of mean SE corresponds to a +2 to -3 dB band on the estimation of DNL or CNEL. However, the fitting of an ARMA model to a time series indicates that that series possesses an autocorrelative structure. Hence, sample sizes determined assuming independence will underestimate, in some cases, by a considerable amount, the actual sample size requirements. When the correlation factors are rightfully applied, the correct sample size requirements emerge. Table 3 lists the sample size requirements for the estimation of the mean noise level for both the cases of assumed independence and correctly accounting for the autocorrelated structure in the data. In

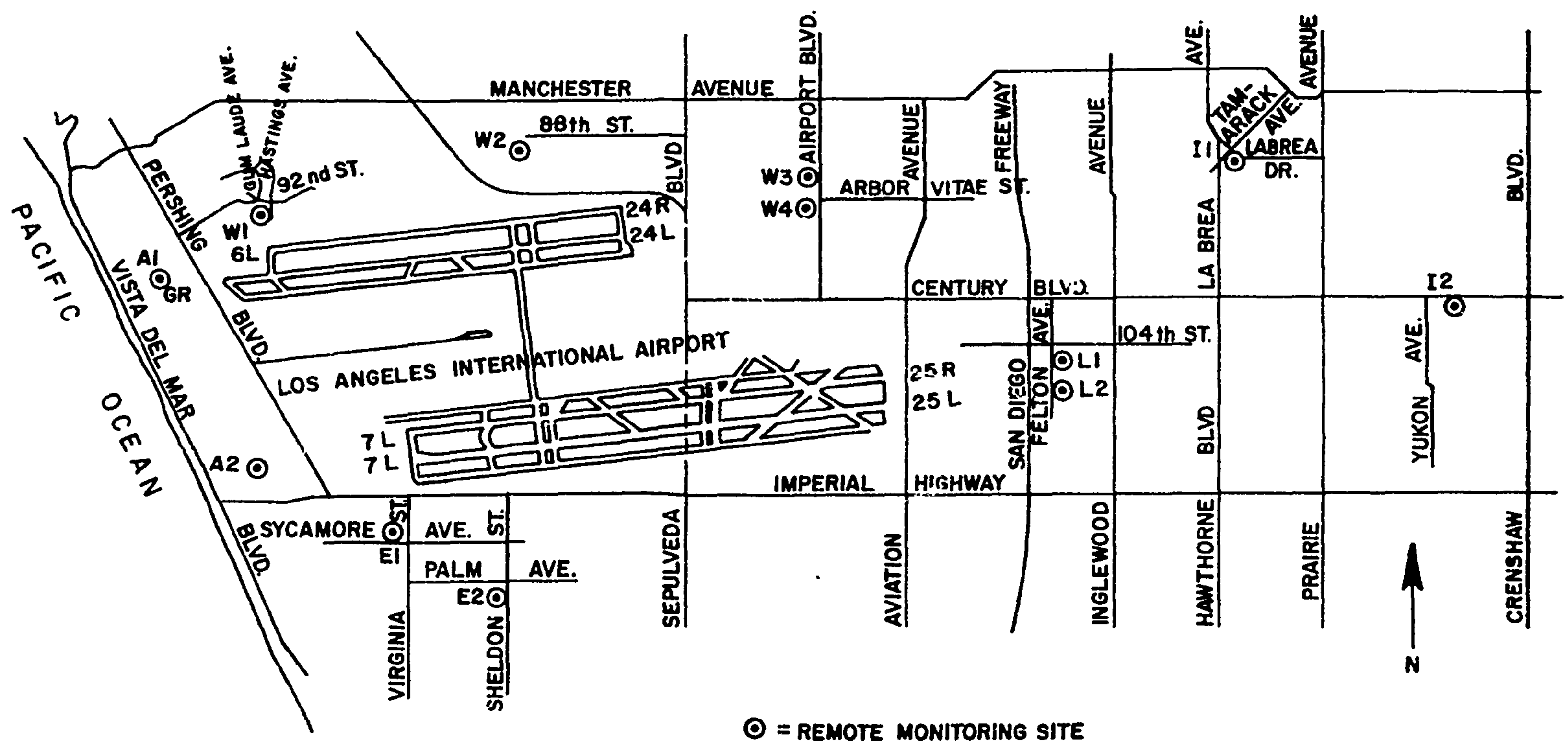

Figure 7. LAX locations of noise monitoring areas.

Table 3

Modeling Results, Summary Statistics, and Sample Size Requirements for Each Site

Site	Model	Mean $\overline{X}$	Variance γ_0	Coefficient of Variation	Auto-Correlation Factor	Sample Size Requirement (Independence)	Sample Size Requirement (Autocorrelation)
A1	ARMA(2,1)	3.89×10^{8}	2.46×10^{16}	0.403	2.140	3	6
A2	ARMA(5,5)	6.60×10^{8}	6.38×10^{16}	0.383	8.189	3	19
E1	AR(1)	3.88×10^{7}	1.17×10^{14}	0.279	3.010	2	4
E2	ARMA(4,3)	1.03×10^{7}	8.76×10^{12}	0.287	5.842	2	8
I2	AR(1)	7.03×10^{7}	6.48×10^{15}	1.140	1.475	20	30
L2	AR(1)	2.27×10^{8}	1.03×10^{16}	0.448	3.353	4	11
W1	ARMA(2,1)	2.21×10^{7}	5.14×10^{13}	0.333	4.980	2	8
W2	Random	7.44×10^{6}	5.71×10^{13}	1.050	1.000	16	16
W3	ARMA(2,1)	8.90×10^{7}	6.85×10^{15}	0.929	4.517	14	60
W4	ARMA(1,1)	5.03×10^{7}	6.12×10^{14}	0.492	2.850	4	11
30*	ARMA(8,7)	1.84×10^{6}	2.535×10^{12}	0.865	1.98	12	23
31*	ARMA(4,3)	1.58×10^{6}	2.332×10^{12}	0.967	2.35	15	33
W50**	ARMA(2,1)	5.19×10^{7}	1.186×10^{15}	0.663	7.48	7	50

Note: Means and variances given in units of mean square pressure.

* Sites at NAS Miramar, California.
** Site at Lindbergh Field, San Diego, California.

the table, the correlation factor relationship is not precisely evident because the sample numbers have been rounded up to the next highest integer in order to guarantee the stated precision. Table 3 also gives summary statistics and sample size requirements for the three monitored sites at NAS Miramar and for the one site at Lindbergh Field. These results are included here to demonstrate the similarity in the results across the three airfields.

In summary, Table 3 lists the monitor sites, the model type, the mean and the standard deviation for the original time series, the coefficient of variation, the number of independent samples required for ±50 percent accuracy (+2 to -3 dB), the correlation factor, and the true number of samples required for ±50 percent accuracy when the autocorrelated nature of the time series is taken into account.

Operational data were also supplied by LAX for landings per day by runways on 25-R, 25-L; 24-R and 24L; and by runway pairs for 6-L and 6-R; and for 7-L and 7-R. Takeoff data were supplied per day by runway pair for 25-L and 25-R; 24-L and 24-R; 6-L and 6-R; and for 7-L and 7-R. Operations at LAX, Miramar, and Lindbergh are typically westward because of prevailing winds off the ocean. Occasionally winds are such that the normal direction of operations must reverse and takeoffs and landings are to the east.

To test the relation of the monitored data at LAX with operations, various correlation pairs were developed (Table 4). In each case, the zeroth-lag cross-correlation between the daily noise level in SE units and the various runway operations in terms of total daily approaches, departures, and the sum of approaches and departures were determined. As can be seen from the descriptions in the table, data pairs were selected to emphasize the predominant type of operation likely to be encountered at any given monitoring location. For example, because of the westbound nature to the traffic flow location, Site L-2 should predominantly measure landings on 25-L and Location E-2 should measure both takeoffs and landings in either direction on the south complex. Table 4 provides only those estimated cross-correlations which were deemed significant in magnitude. While many site noise-operations pairs were correlated, those not found in the table resulted in small (effectively zero) correlation coefficients.

LAX Results

Examination of the data in Table 3 shows a wide range of sampling requirements from site to site, depending on relative location and proximity to the runways. In many cases, the sample size requirements are quite large. The large sample numbers may be caused by the presence of strong positive autocorrelation, large overall noise series variability from day to day, or both. One could hope to observe that the

Table 4

Zeroth Lag Cross-Correlation Between Noise Level Recorded at Site and Operations in the Vicinity of the Site

Site	Operations Strongly Correlated With	Correlation Coefficient
A-1	None	-
A-2	EB/APP/7 + WB/DEP/25	0.481
E-1	WB/APP/25	0.308
	WB/DEP/25	0.312
E-2	WB/APP/25	0.408
	WB/DEP/25	0.323
I-1	WB/APP/24R	0.731
	WB/APP/24	0.639
	WB/APP/24 + EB/DEP/6	0.611
I-2	None	-
L-1	WB/APP/25	0.436
	WB/APP/25 + EB/DEP/7	0.406
L-2	WB/APP/25L	0.716
W-1	None	-
W-2	None	-
W-3	WB/APP/24R	0.678
	WB/APP/24	0.499
	WB/APP/24 + EB/DEP/6	0.439
W-4	WB/APP/24R	0.419
	WB/APP/24	0.432
	WB/APP/24 + EB/DEP/6	0.473

Note: (1) EB/APP/7 + WB/DEP/25 denotes the sum of eastbound approaches on the 7 complex and westbound departures on the 25 complex.

(2) 24R denotes the 24 complex, right runway.

number of required autocorrelated sample days grows smaller as the sample site approaches the airport. Unfortunately, this is not evident since stations A-2, W-2, and W-3 each require substantial numbers of days. However, careful examination of these data, the operational data, and weather conditions indicates possible explanations for the greater variability found in two of these three stations.

Site W-3 has a correlation factor of 4.7, which is typical of the average value found for all the stations in closer proximity to the runways (except for Sites A-2 and W-2, which are the other two sites near the runways which have relatively large sample requirements). Site W-3, however, exhibits a much higher coefficient of variation than do the other sites in the vicinity of the airport (except for Site W-2, which is again one of the three sites under discussion, and Site I-2, which will be discussed later). Examination of the number of landings per day on runway 24-R, the operations which most influence the noise received at Site W-3, indicates a high degree of variation from day to day. The correlation coefficient between the landings on runway 24-R and the noise measured at Site W-3 is 0.678. Although not shown here, the landings on 24-R are much more variable than the landings on the other three runways (24-L, 25-R, and 25-L). Thus, the high coefficient of variation at Site W-3, in reality, reflects the high variation of the operational data which that site is monitoring.

Site A-2 exhibits a coefficient of variation which is much in line with the other stations near the runways (except for Sites W-2 and W-3). At this site, however, the correlation coefficient is 8.2--a value which is much higher than the value of 4 to 5 which is typical of most of the other data (except for Site W-2). Examination of this time series shows that the noise level generally rises during the warm summer months in direct relation to the average daily temperature.[5] This site predominantly measures takeoff noise and is some 4000 ft (1219 m) further from start of roll than is Site A-1. Thus, this site is the only site which will be influenced by the average temperature, since temperature strongly affects the efficiency of the turbojet engines; i.e., turbojets require longer takeoff rolls and thus have lower altitudes over Site A-2 during warm weather. In fact, this is the exact trend strongly evident in the data; i.e., the average sound level goes up during the warm weather months. Referring to Table 4, this conclusion is further supported by the fact that the cross-correlation between the noise level monitored at Site A-2 and the combination of eastbound approaches and westbound departures on the south complex is quite high--a value of 0.481.

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[5] R. E. DeVor, W. A. Kline, and K. M. Tingley, "Analysis of Environmental Noise Data by the Method of Dynamic Data System," Proceedings of the 10th Modeling and Simulation Conference (April 1979), pp 419-428.

Site A-2 exhibits two predominant peaks in the data in addition to the general trend discussed above. One peak appears on May 10 and the other on December 16. Many of the stations exhibit peaks in the mid-to-end of December time period; during this time period there were heavy cloud cover, variable winds, and rain.[6] No explanation can be found in the weather or the operations for the peak exhibited on May 10. Similarly, examination of the data at Site W-2, the other "problem site," shows a very strong peak on July 16. Again, no weather- or operations-related explanation can be found. These two sites were remodeled with these respective days deleted, i.e., July 16 (from Site W-2) and May 10 (from Site A-2).

At Site W-2, removal of the spike on July 16 did not change the model. That is, the site noise series remained totally random and removal of the spike only served to decrease the variance, slightly changing the sampling requirement from 20 days to 16 days. Similarly, at Site A-2, removal of the spike on May 10 did little to change results. However, removing both the spike on May 10 and the spike on December 16 substantially altered the characteristic of the time series, but did little to change the ultimate sampling requirements. Removal of these two spikes revealed a model with a strong deterministic trend. This time series strongly demonstrated a 7-day weekly cycle to the data in addition to the yearly cycle discussed above. Because of this strong weekly cycle, the correlation factor actually rose from its already high value of 8 to almost 25. However, removal of the spike at December 16 may not be justified because its presence can be explained by weather-related factors.

Examination of the cross-correlation data between operations and measured noise levels reveals some correlations to be as expected and others to present some significant departures from expectations. The correlations between noise levels in the vicinity of the east end of the north complex (24) and the corresponding north complex operations exhibit the most regularity and are closest to what was expected. That is, the landings on 24-R correlate highly with the noise measured at Site W-3, the landings on 24-L correlate well with the noise measured at Site W-4, and both sites correlate well with the total operations east of the airport on the north complex. The correlations with Site I-1 indicate that landings on 24-R correlate with these measurements, but the landings on 24-L do not. This also is a reasonable result. It is noted that the cross-correlations between operations on the 24 complex and Site W-2 (to the north side of the complex) are generally small (effectively zero). This site is typified statistically by being a random noise series with a high coefficient of variability (1.05).

Unfortunately, landings on the 25 complex do not exhibit the same regularity and expected results as described above for the 24 complex.

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[6] R. E. DeVor, W. A. Kline, and K. M. Tingley, "Analysis of Environmental Noise Data by the Method of Dynamic Data System," Proceedings of the 10th Modeling and Simulation Conference (April 1979), pp 419-428.

Landings on 25-L correlate well with the noise measured at Site L-2, but landings on 25-R do not correlate with the noise measured at Site L-1. However, the total of all operations to the east of the south complex correlate well with the noise measured at Site L-1. This seems to indicate that Site L-1 is located more nearly acoustically midway between the operations on 25-L and 25-R, rather than as indicated in Figure 7. On the other hand, the lower correlation for Site L-2 with overall operations and the generally higher correlation with the specific landing operations on 25-L indicate that this site is more nearly in line with 25-L. Site I-2 does not correlate with any of the operations, either taken singly or in combination, and like Site W-2, Site I-2's noise series exhibits weak autocorrelation and a high coefficient of variation.

It must be noted that correlations developed between numbers of operations and measured daily noise levels cannot be expected to be extremely high because the measured SE is being correlated with numbers which may represent a variety of noise levels. For example, correlations have been calculated with landings alone, when, in reality, on certain days the landings may be very low and the takeoffs very high, with the resulting noise levels also high. On the other hand, correlations have been developed with total operations where there is no guarantee that these operations do not produce systematically differing noise levels of differing days that is not reflected merely in the total number of operations. As a result, correlation coefficients in excess of about 0.3 are considered significant at this stage of analysis. Based on the amount of data available, correlation coefficients in excess of about ±0.15 would be considered statistically significant. However, for purposes of explaining the data and analysis in this report, only the major significant correlations are presented and discussed.

Sites I-2 and W-2 both exhibit no significant correlation with operations in their vicinity. In addition, they share the same common characteristics of weak or no autocorrelation in the noise series and high levels of variability relative to their mean levels. This raises a question about the actual noise these sites are measuring; i.e., is this monitored noise really strongly related to airport operations? In terms of sampling requirements, however, these sites are quite consistent with the other sites, since while the low autocorrelation tends to reduce the sample size requirements, the high variability brings them back in line with those sites with strong autocorrelation.

LAX Conclusions

In the vicinity of airports, the data indicate that 30 continuous days of monitoring is a reasonable estimate of the number of days required to achieve a precision of +2 to -3dB of the true yearly CNEL (or DNL) value with a 95 percent confidence level. Moreover, the correlation factors appear to be on the order of 4 to 5 in the vicinity of the airport.

However, in worst-case situations--such as when the total operations on a runway become highly variable when long-term weather effects become significant or when there is a weekly cycle to the data--these numbers can become significantly greater than 3 and 4, respectively. These data indicate a worst-case requirement of 60 continuous days in the vicinity of airports, and a worst-case correlation factor on the order of 8.

Because of the correlation factor generally exhibited in most of the noise series, the number of sampling days can be significantly reduced by inducing randomness in the selection of days sampled. That is, sample days can be selected sufficiently far apart to induce randomness in the data gathered, rather than performing continuous monitoring over the total number of days. Because of the long-term seasonal weather effects exhibited in some of these data, it is recommended that samples be selected from throughout the entire year. A variety of strategies can be used based on this analysis. For example, one could:

1. Sample for a continuous period of 30 to 60 days.

2. Sample 14 days chosen randomly throughout the year (using different days of the week.

3. Sample for four 1-week periods--each chosen from a different season.

The above can be summarized as a recommendation for using 14 days of totally random sampling throughout the year, or 4 weeks of quasi-random sampling taken 1 week at a time from each season, or 8 weeks of totally continuous sampling to achieve a precision of +2 to -3 dB of the true yearly CNEL or DNL at a 95 percent level of confidence.

Boston Logan

Continuous daily monitored DNL values were supplied for the 15 sites at Boston Logan International Airport from October 1, 1978 to October 31, 1979 (Figure 8). Because of the close correspondence between the units of CNEL and DNL, the conclusions given below are equally applicable to both.

The time series at some locations were divided into Part A and Part B at a convenient gap around the halfway mark in the data. This was done to split up the rather large number of observations. Using the DDS approach to time series analysis, ARMA models were derived for all the monitoring sites. The estimated parameters were used to determine the correlation factor and the appropriate sampling requirements for mean-level estimation, correctly accounting for the autocorrelation in the data.

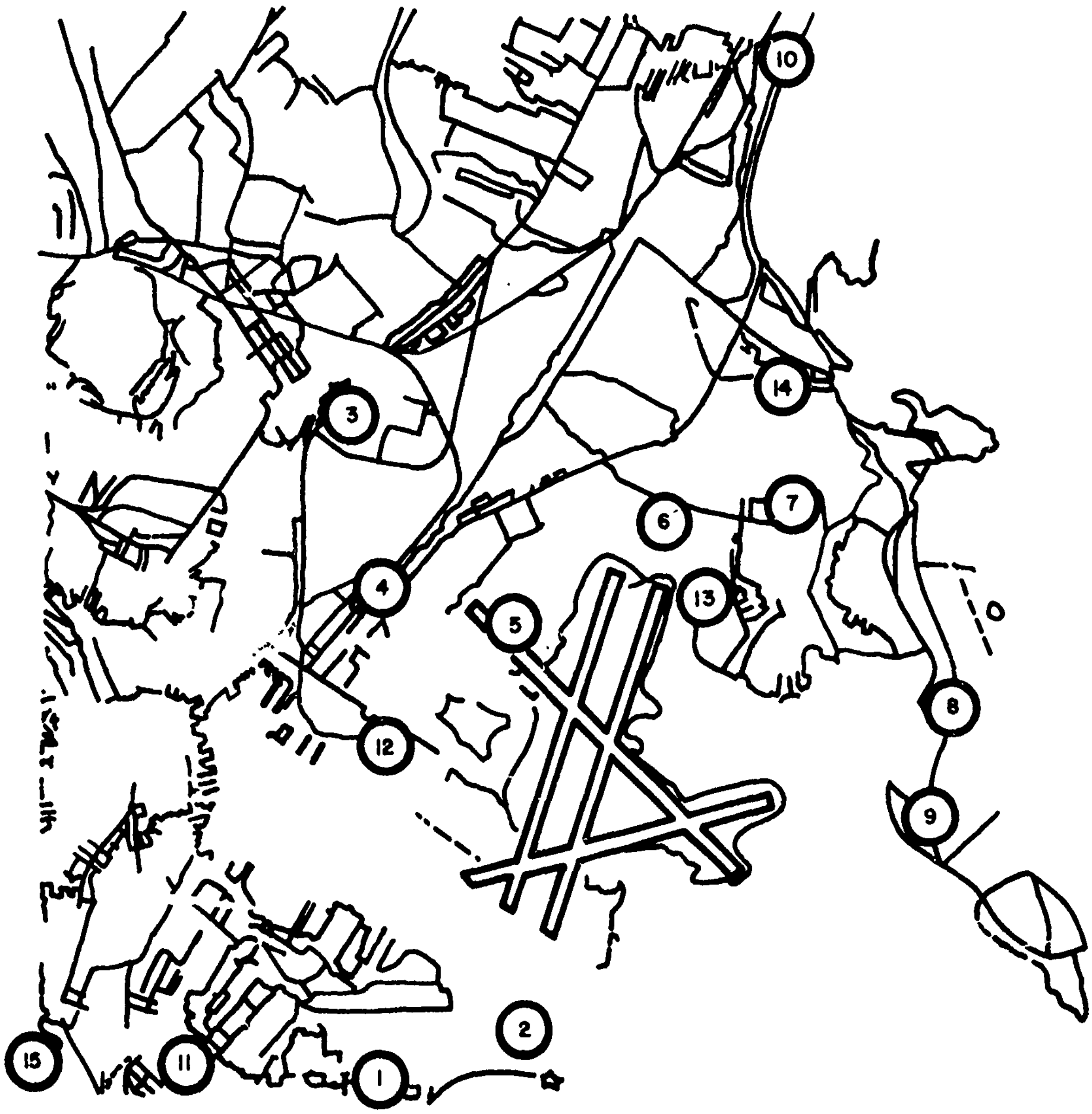


Figure 8. Boston Logan International Airport--locations of noise monitoring sites.

Figure 8. (Cont'd).

Runway operations data were unavailable at Boston Logan, but all the sites were evaluated and the monitored levels found to exceed reasonable estimates of the community noise in the absence of aircraft. Thus, the monitored data were assumed to be predominantly aircraft noise and subject to a constant set of prevailing operations. All the time series were found to be stationary, i.e., fluctuating about a fixed mean with a relatively constant pattern of irregularity, usually strong positive autocorrelation.

Boston Logan Results

Frequency histograms and time series plots are shown in Appendix B, and the DDS modeling results are listed in Table 5 for all sites at Boston. Most of the data were fit to low order AR(1) time series models, with correlation factors commonly ranging from 1.5 to 2.5. The required sample sizes for estimation of the mean within a ±50 percent $\overline{X}$ (+2, -3 dB) range at 95 percent confidence commonly varied from 10 to 60 days. Site 4A was the only exception, with a very high correlation factor of 6.35 and a correspondingly large sample size of 134. However, Sites 3 and 5 (in the same general area) also have much higher than average correlation factors and sampling requirements. Perhaps this is caused by fluctuating operations on runway 33L. Almost all the data have a 15 to 20 dB spread from the minimum to maximum value, and the coefficient of variation commonly ranges from 0.8 to 1.0. Site 11 has an unexpectedly high mean considering its rather remote location.

Washington National and Dulles

Data were analyzed from Washington National and Dulles airports for the period of March 17, 1978 to December 14, 1979. At Dulles airport, the daily number of arrivals and departures are significantly less than at Los Angeles or Boston, and for both Washington airports, the monitoring sites were generally positioned farther from the airport (see Figures 9 and 10). For these reasons, it was attempted to determine whether each site was monitoring predominantly aircraft or community noise. Frequency histograms and time series plots for both airports are shown in Appendix C.

Monthly Federal Aviation Administration (FAA) noise level plots (Figure 11) served as the basis for this classification process. The sample plot in Figure 11 shows the airport noise level (indicated by the horizontal hatching) standing clearly above the background community noise level of about 65 dB. Plots of this type were studied for all of the National and Dulles sites. In some cases, a site could be unquestionably classified as an airport or a community noise site, but it was necessary to classify some sites as mixed airport and community noise sites.

Table 5

Boston Logan--DDS Modeling Results

Site	Model	Mean $\bar{X}$	Variation γ_o	Coefficient of Variation	Correlation Factor	Sample Size
1A	AR(1)	1.08×10^{7}	5.28×10^{13}	0.68	1.94	17
1B	AR(1)	1.09×10^{7}	3.73×10^{13}	0.56	1.31	7
2	ARMA(3,2)	3.59×10^{7}	1.29×10^{15}	0.47	3.03	50
3A	AR(1)	8.48×10^{6}	5.27×10^{13}	0.86	2.48	29
3B	ARMA(3,1)	6.85×10^{6}	3.37×10^{13}	0.85	4.11	48
4A	ARMA(2,1)	2.72×10^{7}	9.72×10^{14}	1.15	6.35	134
4B	ARMA(2,1)	1.80×10^{7}	2.98×10^{14}	0.93	3.85	54
5A	AR(1)	2.10×10^{8}	3.35×10^{16}	0.88	2.51	32
5B	AR(1)	2.66×10^{8}	4.95×10^{16}	0.84	2.48	29
6A	AR(1)	4.84×10^{7}	3.06×10^{15}	1.14	2.50	53
6B	White Noise	7.16×10^{7}	7.80×10^{15}	1.24	1.00	25
7	AR(1)	9.34×10^{6}	8.76×10^{13}	0.99	1.61	26
8A	AR(1)	3.83×10^{7}	1.21×10^{15}	0.87	1.95	27
8B	AR(1)	2.94×10^{7}	6.86×10^{14}	0.90	1.94	25
9	AR(1)	3.07×10^{7}	2.24×10^{15}	1.56	1.64	64
10	White Noise	6.50×10^{7}	3.81×10^{13}	0.21	1.00	16
11	AR(1)	7.65×10^{6}	5.49×10^{13}	0.98	1.43	22
12	AR(1)	2.06×10^{7}	3.46×10^{14}	0.91	1.44	20
13	AR(1)	2.82×10^{7}	5.68×10^{14}	0.84	1.34	16
14	AR(1)	3.26×10^{7}	2.18×10^{15}	1.43	2.05	68
15	AR(1)	1.76×10^{7}	2.27×10^{14}	0.85	1.99	24

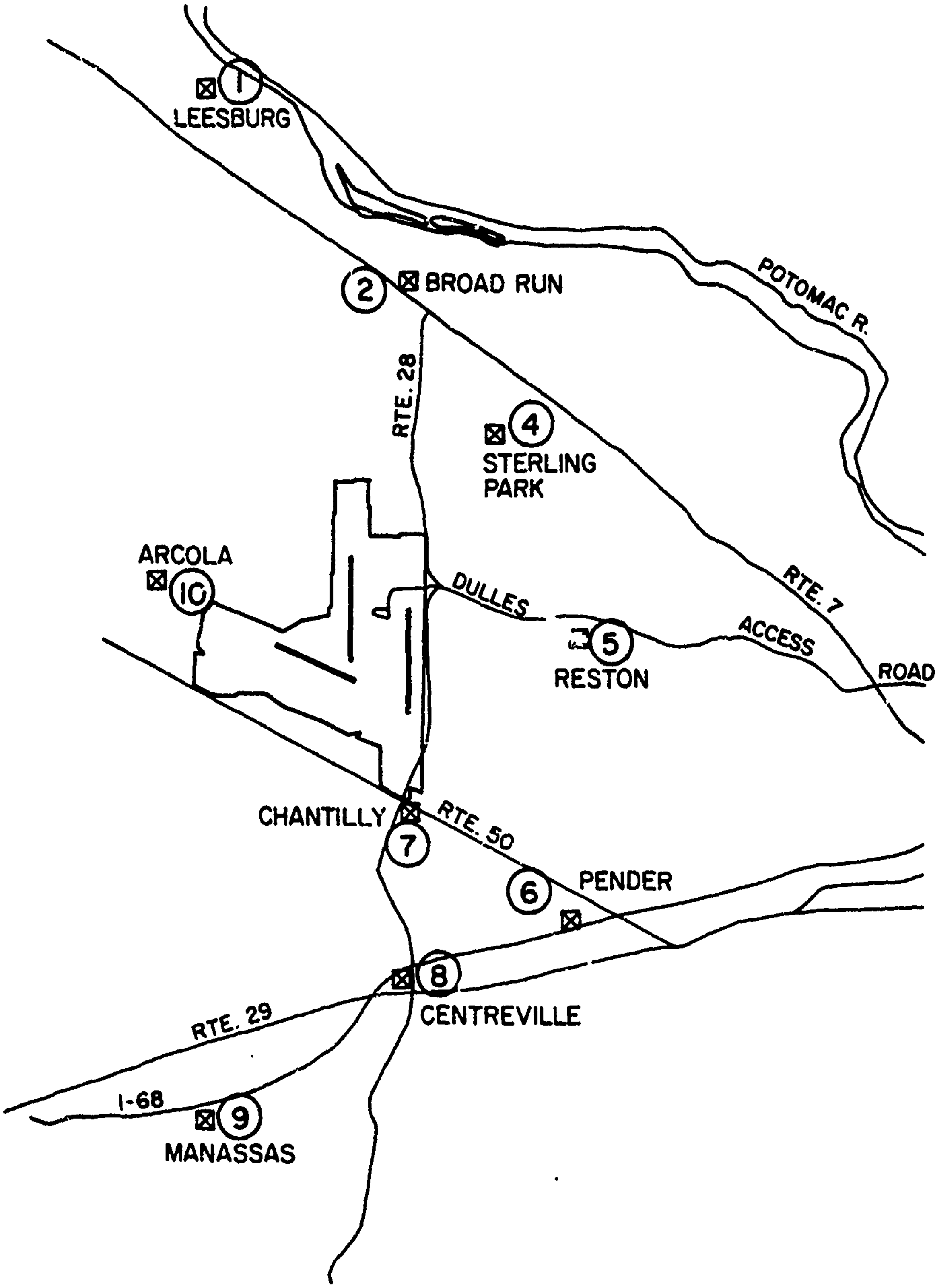


Figure 9. Washington Dulles International Airport--locations of noise monitoring sites.

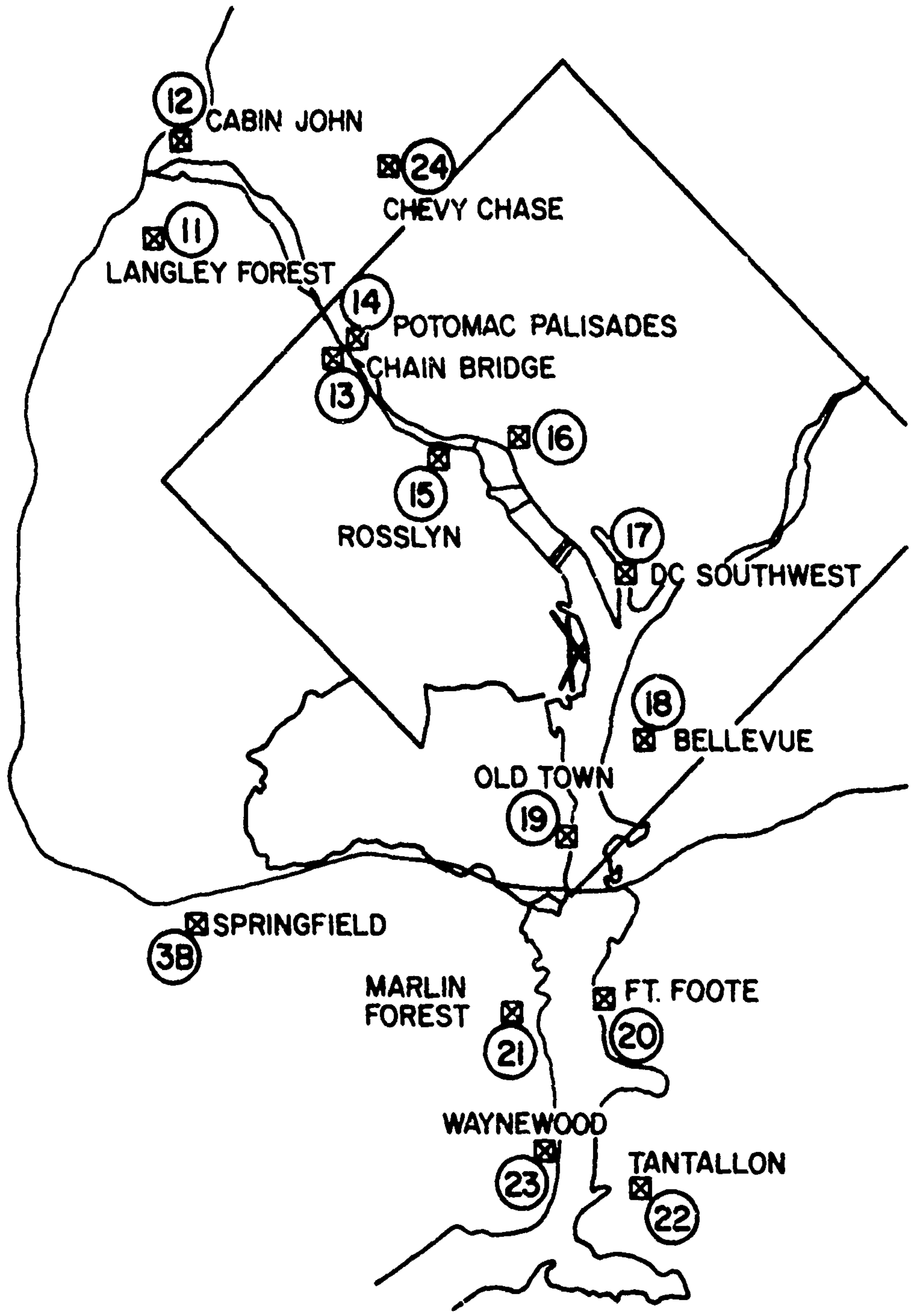


Figure 10. Washington National Airport--locations of noise monitoring sites.

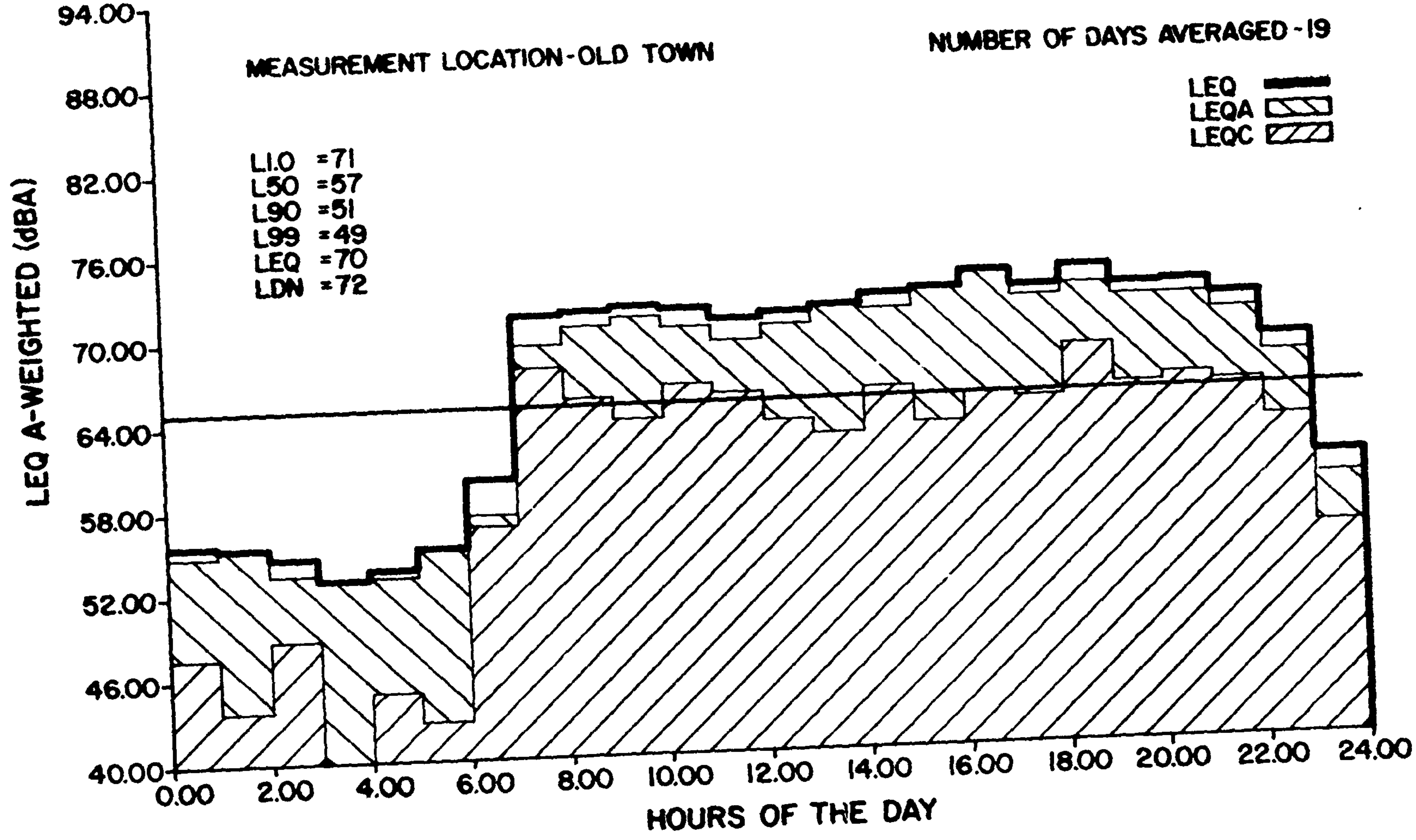


Figure 11. Average hourly noise levels for month of October 1978 -- Washington National and Dulles.

DDS modeling was performed for each site. Site classification and modeling results are summarized in Tables 6, 7, and 8. Low-order models resulted for most of the sites, with a first-order autoregressive model, AR(1), being common. The sampling requirements for the Washington airport sites cover a wide range--from N=7 at Site 7A to N=54 at Site 13A. The community and mixed sites also exhibit a wide range of sampling requirements similar to the airport sites.

The availability of the FAA noise level plots made possible a sensitivity analysis of the DDS modeling approach. The sites classified as airport sites actually consist of days of airport noise, and days with little airport activity where the background community noise is measured. The FAA reports were used to identify an average community noise level for each airport site. Values in the time series below this cutoff level were set to an insignificant level, i.e., 40 dB. Thus, a time series of only airport noise events results. This new series was modeled by DDS and the sampling requirements derived. The effect of uncertainties in the cutoff level was explored by selecting cutoff values at -3, +3, and +6 dB from the average community noise level in addition to the average community noise level. Table 9 summarizes the modeling results and sampling requirements for the cutoff experiments. The "Number of Points" column in the table is the number of points in the time series remaining above the cutoff level. Figure 12 summarizes the sampling requirements for the cutoff experiments. For the -3, 0, and +3 cutoffs, the number of points did not change significantly from the original times series: the time series models and sampling requirements also did not change significantly. For the +6 dB cutoffs, the number of points remaining is greatly reduced: in some cases, this resulted in increased sampling requirements because of the increase in coefficient of variation. This experiment indicate that (1) the majority of the data for the airport sites are airport noise, and (2) the DDS modeling approach and resulting sampling requirements are insensitive to the "bottom floor" of the data, i.e., the autocorrelated structure and coefficient of variation is largely determined by the loud noise events.

Analysis of Airport Data Summary

As a result of the modeling and analysis of the noise data for Los Angeles, Boston, and Washington, a number of comparisons and contrasts may be made.

1. The sampling requirements for the Los Angeles and the Washington airports are somewhat similar in that a wide range of requirements exists. At Los Angeles, the sampling requirements range from 4 to 60 consecutive days. For the Washington airport sites, the requirements range from 6 to 54 consecutive days.

Table 6

Washington National and Dulles Aircraft Sites --
DDS Modeling Results on Original Data

Airport	Site	Model	Mean $\bar{X}$	Variation γ_0	Coefficient of Variation	Correlation Factor	Sample Size
Dulles	7A	AR(1)	3.08×10^7	2.41×10^{14}	0.51	1.49	7
Dulles	7B	AR(1)	2.86×10^7	3.35×10^{14}	0.65	2.50	17
National	13A	White Noise	6.12×10^6	1.25×10^{14}	1.83	1.00	54
National	13B	AR(2)	5.59×10^6	1.37×10^{13}	.66	3.25	23
National	14A	AR(1)	4.45×10^6	4.47×10^{12}	.47	1.49	6
National	14B	AR(1)	6.32×10^6	1.51×10^{13}	.62	3.09	19
National	15A	Whit Nois	1.25×10^7	1.15×10^{14}	0.86	1.00	13
National	15B	AR(1)	1.36×10^7	1.17×10^{14}	0.80	1.79	19
National	16B	AR(1)	6.09×10^6	1.05×10^{13}	0.53	2.56	12
National	19B	AR(1)	1.59×10^7	2.14×10^{14}	0.92	1.82	25

Table 7

Washington National and Dulles Community Sites -- DDS Modeling Sites

Airport	Site	Model	Mean $\bar{X}$	Variation γ_0	Coefficient of Variation	Correlation Factor	Sample Size
Dulles	1A	White Noise	6.19×10^5	1.01×10^{11}	0.52	1.00	5
Dulles	1B	AR(1)	9.07×10^5	7.52×10^{11}	0.95	2.06	31
Dulles	4A	Non-stationary	6.44×10^6	$1.11.15 \times 10^{13}$	0.53	--	--
Dulles	5A	AR(3)	2.40×10^6	2.33×10^{12}	0.64	10.28	67
Dulles	9A	AR(1)	3.94×10^6	3.54×10^{12}	0.48	1.77	7
National	24B	AR(1)	1.68×10^6	4.75×10^{11}	0.43	5.14	14

Table 8

Washington National and Dulles Mixed Sites -- DDS Modeling Results

Airport	Site	Model	Mean $\bar{X}$	Variation γ_o	Coefficient of Variation	Correlation Factor	Sample Size
National	3B	AR(2)	2.57×10^6	1.58×10^{13}	0.36	2.65	6
Dulles	6A	White Noise	2.46×10^7	1.30×10^{13}	1.47	1.00	5
Dulles	6B	AR(1)	1.24×10^6	2.14×10^{11}	0.37	2.11	5
Dulles	8A	White Noise	3.44×10^7	5.32×10^{12}	0.67	1.00	9
Dulles	8B	White Noise	3.51×10^6	6.83×10^{12}	2.02	1.00	70
Dulles	10A	AR(1)	1.29×10^7	9.68×10^{13}	0.76	2.62	25
Dulles	10B	Non-stationary	1.32×10^7	6.64×10^{13}	0.62	--	--
National	11	ARMA(2,2)	1.77×10^6	1.99×10^{12}	0.80	11.00	112
National	12	AR(2)	2.97×10^{16}	3.70×10^{12}	.0.65	3.80	26
National	18	White Noise	7.44×10^5	4.69×10^{13}	0.92	1.00	14
National	20A	White Noise	5.37×10^6	2.11×10^{13}	0.85	1.00	11
National	20B	AR(1)	4.59×10^6	5.47×10^{12}	0.51	1.67	7
National	21A	Non-stationary	1.69×10^6	1.11×10^{12}	0.62	--	--
National	21B	AR(1)	1.78×10^6	3.38×10^{12}	1.03	1.85	32
National	22A	AR(1)	1.98×10^6	2.69×10^{12}	0.83	1.30	15
National	22B	AR(2)	1.94×10^6	2.41×10^{12}	0.80	4.83	50

Table 9

Washington National and Dulles Aircraft Sites -- DDS Modeling Results With Cutoffs

Airport	Site	Cutoff	Number of Points.	Model	Mean $\bar{X}$	Variation γ_0	Coefficient of Variation	Correlation Factor	Sample Size
Dulles	7A	60	150	AR(1)	3.08×10^{7}	2.41×10^{14}	0.51	1.49	7
		63	150	AR(1)	3.08×10^{7}	2.41×10^{14}	0.51	1.49	7
		66	149	White Noise	3.06×10^{7}	2.42×10^{14}	0.51	1.00	7
		69	149	White	3.06×10^{7}	2.42×10^{14}	0.51	1.00	7
Dulles	7B	60	150	AR(1)	2.86×10^{7}	3.35×10^{14}	0.65	2.50	17
		63	149	AR(1)	2.85×10^{7}	3 [illegible] $\times 10^{14}$	0.65	2.50	17
	.66	146	AR(1)	2.83×10^{7}	3.39×10^{14}	0.66	2.52	18	
	.69	133	AR(1)	2.78×10^{7}	3.62×10^{14}	0.69	2.59	20	
National	13A	57	150	White	Noise 6.12×10^{6}	1.25×10^{4}	1.83	1.00	54
		60	142	White Noise	6.08×10^{6}	1.25×10^{14}	1.83	1.00	55
		63	125	White Noise	5.91×10^{6}	1.27×10^{14}	1.90	1.00	59
		66	75	White Noise	5.03×10^{6}	1.34×10^{14}	2.29	1.00	86
National	13B	57	150	AR(2)	5.59×10^{6}	1.37×10^{13}	0.66	3.25	23
		60	149	AR(2)	5.59×10^{6}	1.38×10^{13}	0.67	3.25	23
		63	139	AR(1)	5.49×10^{6}	1.47×10^{13}	0.70	2.23	18
		66	99	AR(2)	4.78×10^{6}	2.00×10^{13}	0.94	3.11	44
National	14A	57	150	AR(1)	4.45×10^{6}	4.47×10^{12}	0.47	1.49	6
		60	0.48	AR(1)	4.44×10^{6}	4.72×10^{12}	.48	1.46	6
		63	147	AR(1)	4.43×10^{6}	4.79×10^{12}	0.48	1.46	6
		66	93	Non-stationary	3.51×10^{6}	9.51×10^{12}	0.88	--	--

Table 9 (Cont'd)

Airport	Site	Cutoff	Number of Points	Model	Mean $\bar{X}$	Variation Y_0	Coefficient of Variation	Correlation Factor	Sample Size
National	14B	57	150	AR(1)	6.32×10^6	1.51×10^{13}	0.62	3.09	19
		60	149	AR(1)	6.31×10^6	1.55×10^{13}	00.62	3.09	19
		63	147	AR(1)	6.29×10^6	1.57×10^{13}	0.62	3.09	20
		66	111	AR(1)	5.68×10^6	2.15×10^{13}	0.81	3.05	33
National	15A	58	150	White Noise	1.25×10^7	1.15×10^{14}	0.86	1.00	13
		61	148	White Noise	1.25×10^7	1.17×10^{14}	0.85	1.00	13
		64	147	White Noise	1.25×10^7	1.18×10^{14}	0.85	1.00	13
		67	120	White Noise	1.19×10^7	1.30×10^{14}	0.94	1.00	16
National	15B	58	150	AR(1)	1.36×10^7	1.17×10^{14}	0.80	1.79	19
		61	149	AR(1)	1.36×10^7	1.19×10^{14}	0.80	1.78	19
		64	143	AR(1)	1.35×10^7	1.20×10^{14}	0.81	1.80	19
		67	124	AR(1)	1.31×10^7	1.31×10^{14}	0.87	1.87	23
National	16B	58	150	AR(1)	6.09×10^6	1.05×10^{13}	0.53	2.56	12
		61	150	AR(1)	6.09×10^6	1.05×10^{13}	0.53	2.56	12
		64	140	AR(1)	5.96×10^6	1.21×10^{13}	0.58	2.59	14
		67	101	AR(1)	5.10×10^6	1.87×10^{13}	0.84	2.47	28
National	19B	61	150	AR(1)	1.59×10^7	2.14×10^{14}	0.92	1.82	25
		64	143	AR(1)	1.59×10^7	2.16×10^{14}	0.93	1.82	25
		67	116	AR(1)	1.52×10^7	2.34×10^{14}	1.00	1.88	31
		70	72	AR(3)	1.31×10^7	2.78×10^{14}	1.28	3.69	97

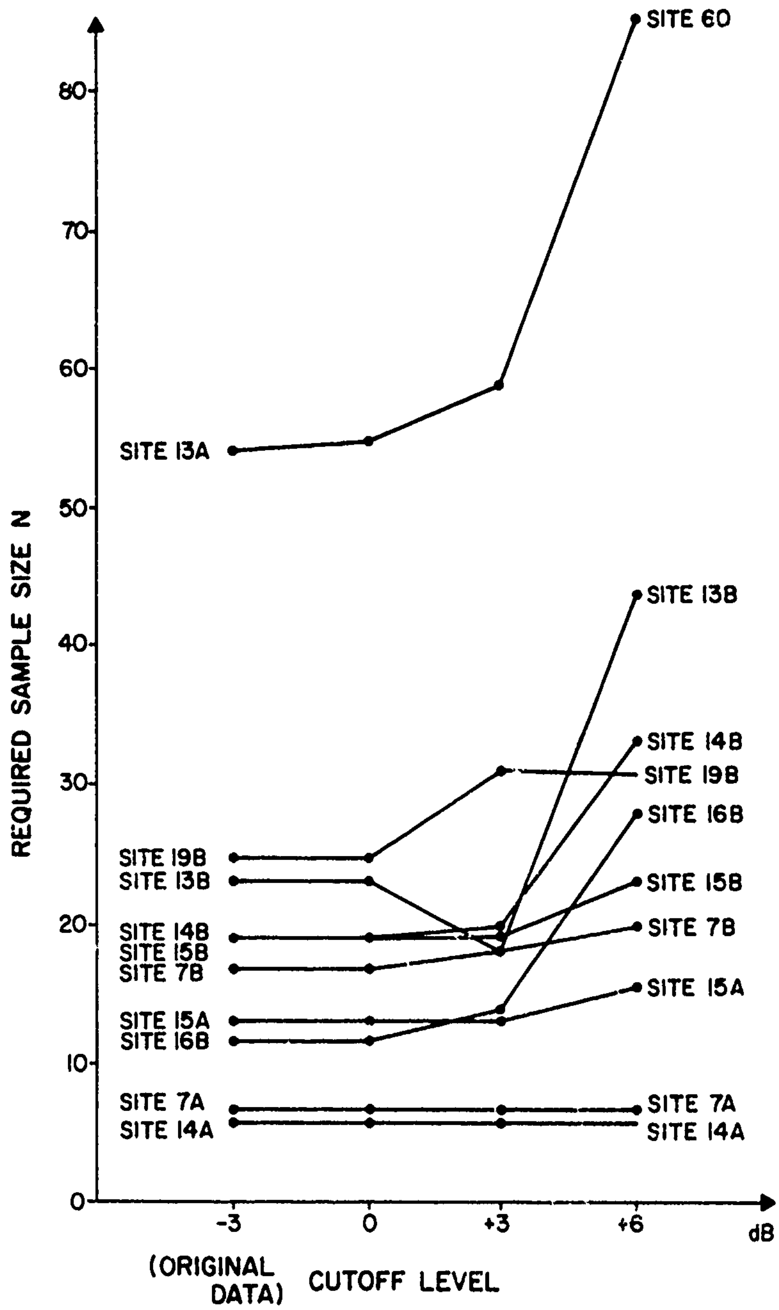


Figure 12. Washington Airport noise sites sampling requirements at varying cutoff levels.

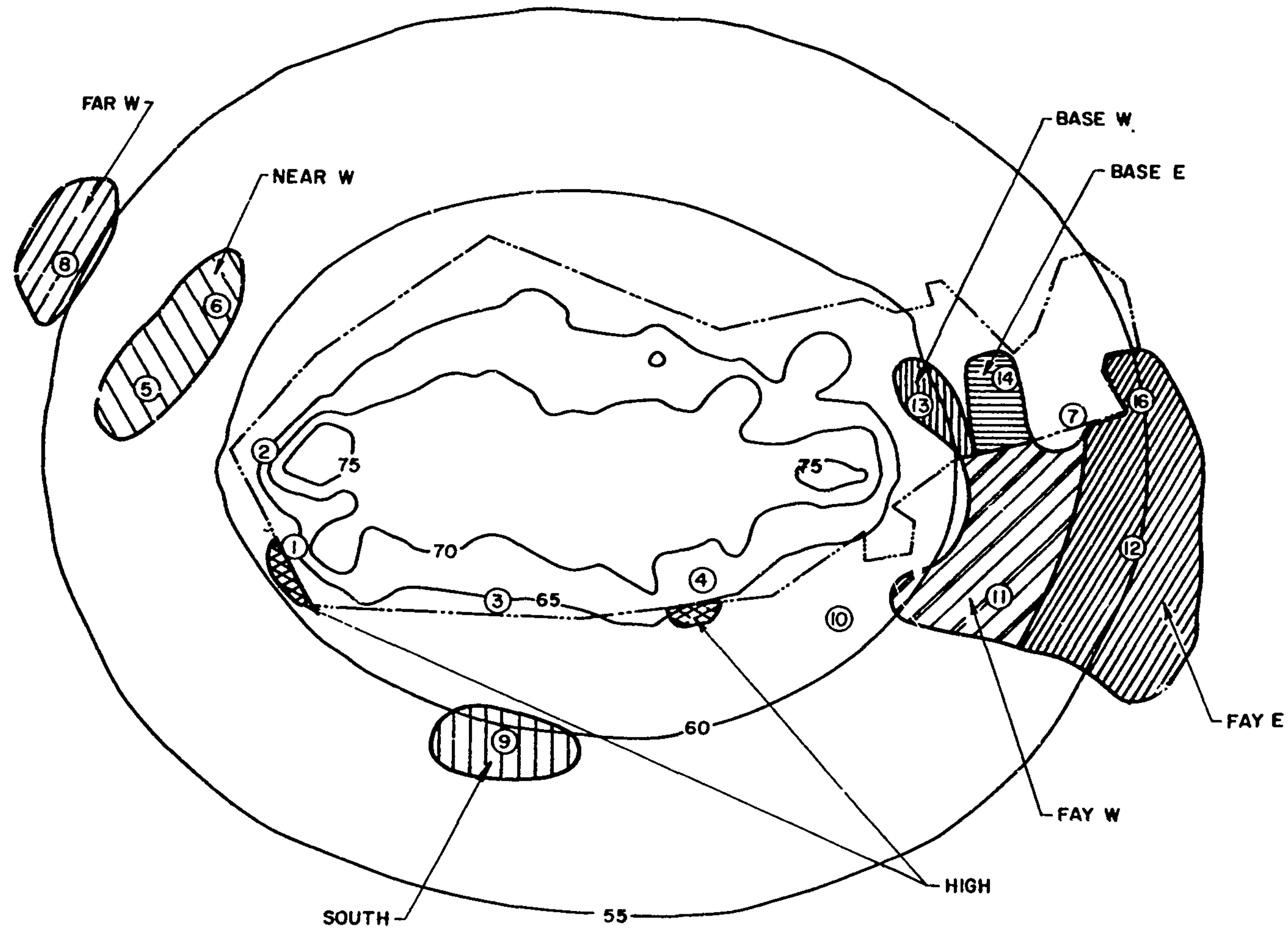


Figure 13. Fort Bragg military installation blast noise monitoring sites. (Sites 15 and 17 measure only aircraft noise.)

2. The sampling requirements for Boston also cover a wide range--7 to 134 consecutive days--but on the average, the requirements are greater than at Los Angeles or Washington. At Boston, sampling requirements of 20 to 50 consecutive days are representative, while at Los Angeles and Washington, requirements from 10 to 30 are representative.

3. The sites classified as community and mixed noise sites at Washington exhibit sampling requirements similar to the requirements for the sites classified as airport noise sites.

4. By examining two coefficients of variation, it can be observed in Tables 3, 5, 6, 7, and 8 that the coefficients at the "multirunway" Boston airport, on average, tend to be larger and the variation from site to site is smaller than at the "single" runway airports (i.e., Los Angeles, National, and to an extent, Dulles). Furthermore, the correlation factors tend to be smaller and, again, more uniform from site to site at multirunway Boston than at the single runway airports. The net result of these observations is that the sampling requirements at multirunway Boston are less site-sensitive owing to this regularity in requirements from site to site.

4 FORT BRAGG OPERATIONS DATA

The noise situation at the Fort Bragg military installation is quite different than at the large commercial airports discussed in Chapters 2 and 3. At Fort Bragg, the high sound exposures are produced by impulse noise such as artillery and demolition. The data analyzed at Fort Bragg were obtained from a computerized model developed by CERL for predicting C-weighted DNL (CDNL) contours based solely on the operations at Army installations. This program operates in a fashion analogous to other noise contouring programs, but is designed to implement the National Academy of Science's recommended procedures for assessing impulse noise. Basically, the National Academy of Science procedure uses C-weighting and predicts a CDNL, including a 10-dB nighttime penalty. This formulation discards single-event SELS that are less than 85 dB during the daytime and less than 75 dB at night. Figure 13 shows these contours for the Fiscal Year 1978 (FY78) preceding the survey in the study area.

Results at Fort Bragg

As can be seen from Figure 14, the operations and resulting noise values at a typical site are highly variable. There are many (20 to 35 percent) "zero" days, i.e., days on which no firing takes place (usually Saturdays and Sundays). This is seen in the time series plots (Figure 14 and Appendix D) which contain many large spikes. The distribution of the noise values for a typical site (Figure 15) has a lower mean than the airport sites studied, and is strongly negatively skewed to the left. This gave rise to large coefficients of variation ranging from 1.53 to 3.22. Higher-order models such as ARMA(5,3) and ARMA(4,3) were necessary to adequately describe the data as summarized in Table 10. These models have correlation factors which are quite large, ranging from 2.6 to 7.4. As a result, the sampling requirements necessary to estimate the long-term mean within ±50 percent in energy units range from 133 to 821.

It is interesting to note that neighboring sites exhibit similar models and sampling requirements. For example, Sites 7, 11, 12, 13, 14, 16, and 17 are neighboring sites--all are modeled by ARMA(5,3) and all have similar coefficients of variation and correlation factors.

It is possible to significantly reduce the extremely large sampling requirements present at Fort Bragg by using a variance reduction technique called "importance sampling." This technique concentrates the sampling effort on those values or ranges of a random variable that are most likely to occur, or on those that have a small probability of occurrence, but are the value of real concern. If the "zero" days or all Saturdays and Sundays are removed and the time series compressed, the required sample size (in real time, including days when no sampling was

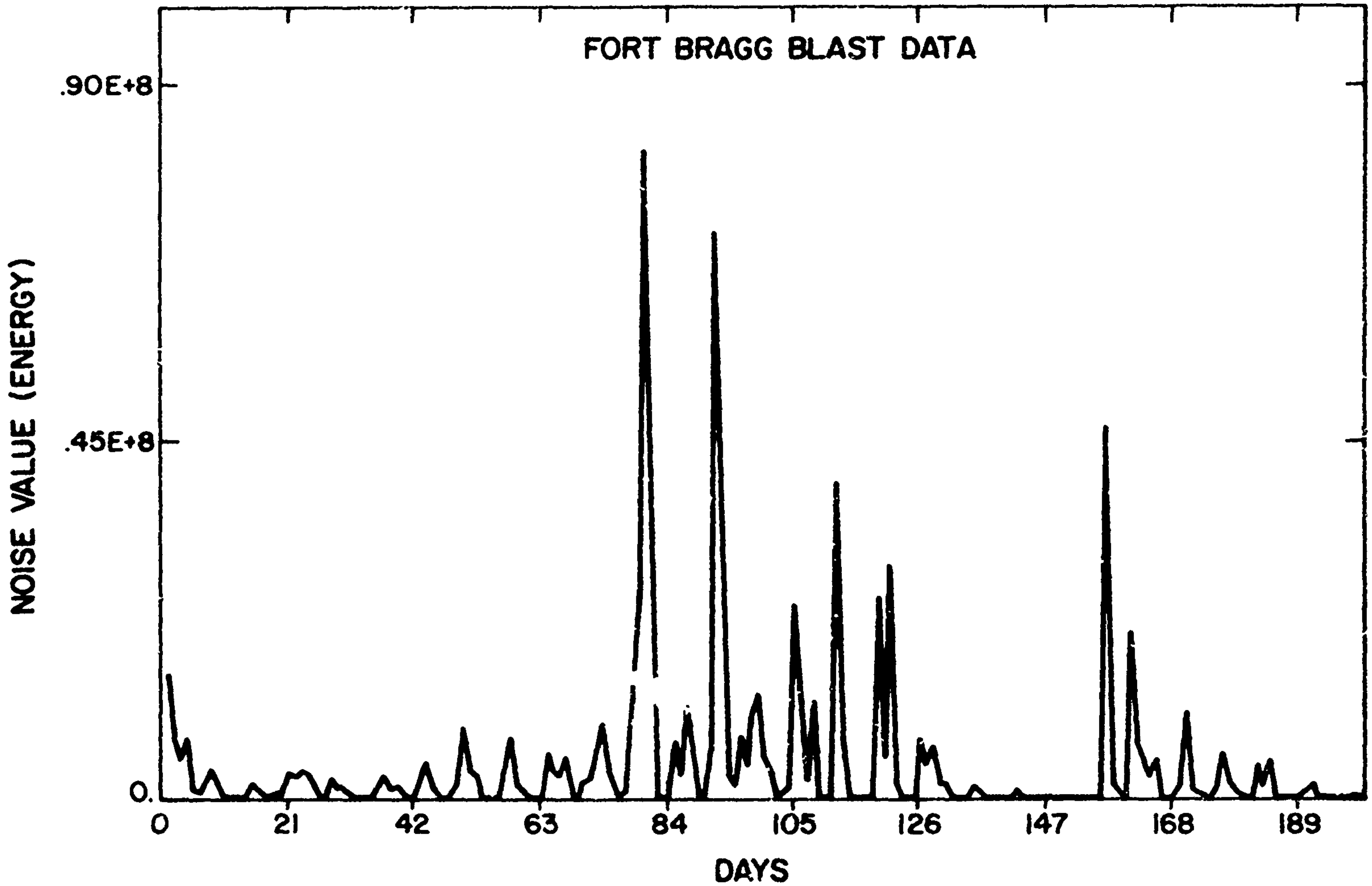


Figure 14. Time series plot -- Fort Bragg data.

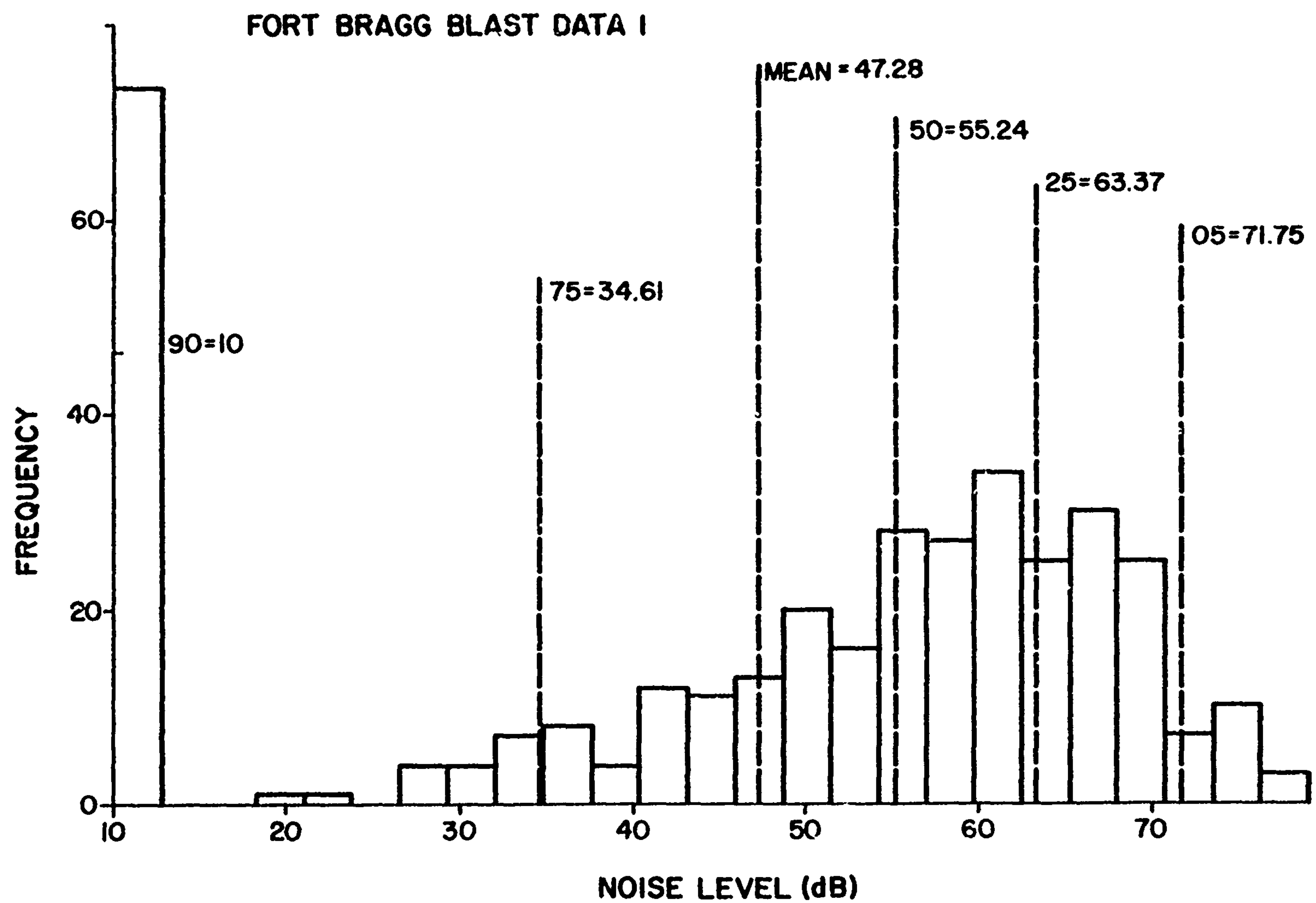


Figure 15. Distribution of noise values for a typical site -- Fort Bragg.

Table 10

Fort Bragg Military Installation -- DDS Modeling Results

Site	Model	Mean $\overline{X}$	Variation γ_0	Coefficient of Variation	Correlation Factor	Sample Size
1	ARMA(5,3)	3.19×10^6	7.61×10^{13}	2.73	6.85	821
2	ARMA(5,4)	2.94×10^6	8.94×10^{13}	3.22	3.33	552
3	ARMA(3,2)	3.28×10^{13}	3.91×10^{13}	1.91	6.37	371
4	ARMA(4,3)	4.57×10^6	5.67×10^{13}	1.65	4.20	183
5	ARMA(4,3)	6.70×10^6	1.54×10^{12}	1.85	7.31	403
6	ARMA(4,3)	9.39×10^5	3.08×10^{12}	1.87	7.37	413
7	ARMA(5,3)	5.81×10^5	1.06×10^{12}	1.78	3.79	192
8	ARMA(6,5)	[illegible]39 $\times 10^5$	4.97×10^{11}	1.81	7.30	383
9	ARMA(5,3)	1.03×10^6	3.06×10^{12}	1.70	6.80	316
10	ARMA(5,3)	1.74×10^6	7.13×10^{12}	1.53	3.53	133
11	ARMA(5,3)	6.00×10^5	1.01×10^{12}	1.67	3.85	173
12	ARMA(5,3)	4.21×10^5	6.25×10^{11}	1.88	4.24	239
13	ARMA(5,3)	1.60×10^6	8.27×10^{12}	1.80	2.59	135
14	ARMA(5,3)	8.00×10^5	1.86×10^{12}	1.70	3.49	163
15	ARMA(5,3)	7.78×10^5	1.66×10^{12}	1.66	3.90	172
16	ARMA(5,3)	4.03×10^5	5.89×10^{11}	1.90	4.27	248
17	ARMA(5,3)	4.48×10^5	6.80×10^{11}	1.84	4.21	229

done) may be reduced up to 50 percent. Of course, this technique introduces a bias in the estimation of the mean, but this is easily corrected by appropriately adjusting the mean downwards. An even greater improvement can be accomplished by not sampling on days below the median (L_{50}), but these times would be difficult to accurately predict in advance. Also, the bias in the mean would have to be approximated because the values of the eliminated data points are unknown.

Variance reduction techniques such as importance sampling are potentially powerful additional tools applicable to the noise sampling problem. This study did not extensively use the idea of importance sampling, but in further investigations it might be used to great advantage to decrease the required sample size for mean-level estimation.

Summary

It is important to realize that the noise values at Fort Bragg are based only on operations and do not take the weather effects into account. Consequently, the predicted and measured noise values are distorted, causing inaccurate and imprecise estimates of the mean level. In Chapter 5, a combined model is developed which uses the airport data as a weather model, and together with the operations component, more realistically assesses the sampling requirements for Army installations.

5 MULTIPLICATIVE MODEL FOR BLAST OPERATIONS AND WEATHER

The data analyzed for the Fort Bragg sites are theoretical values based on the levels of firing activity at the installation. The development of meaningful sampling strategies for these data requires that the effects of weather be properly accounted for. A multiplicative relationship between the blast noise and weather effects is proposed as shown in Figure 16. The weather serves to modulate the blast noise in the energy domain, or equivalently, the weather has an additive effect in decibel units.

The parametric nature of the time series models developed in this report facilitates the calculation of the statistics of the product of the blast operations and weather processes necessary to derive sampling strategies. It is assumed that the time series models developed in this report for airport noise are representative of weather effects. In reality, the airport monitoring sites measure aircraft operations' noise and the patterns of the operations are influenced by weather effects. The large commercial airports discussed in Chapter 3 exhibit a fairly constant level of daily activity, so variations in the day-to-day sound levels may be attributed to weather effects. In many cases, the appropriate model for the airport data is a first-order autoregressive model, AR(1), with a ϕ ranging from 0.25 to 0.4. This model structure also has intuitive appeal for characterizing weather effects. This model structure says that the weather conditions today are a fraction, ϕ, of the weather effects yesterday plus a random term. Because of its simplicity and intuitive appeal, an AR(1) model structure was used in the development of a multiplicative blast times weather model.

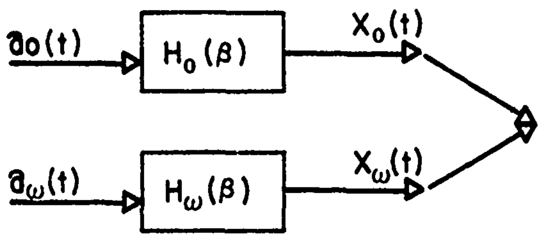
As outlined in Chapter 2, in order to derive sampling requirements for the mean noise level, an estimate of the variance of the sample mean is required. The general equation for the sample mean variance is:

$$\mathrm{VAR}(\overline{X}) = \frac{1}{N} \sum_{k=-\infty}^{\infty} \gamma_X(k) \qquad \text{[Eq 21]}$$

where $\gamma_X(k)$ is the autocovariance function of X(t) at lag k.

N is the number of samples.

For the multiplicative blast times weather process, X(t), it is necessary to derive the mean and autocovariance function of X(t) in terms of the means and autocovariance functions of the component blast and weather processes.



where $\alpha_o(t)$ and $\alpha_\omega(t)$ are the white noise processes for the blast operations and weather $\alpha_o(t)$ and $\alpha_\omega(t)$ are independent processes

H_o (β) and $H_\omega(\beta)$ are the time series models for the blast operations and weather

$X_o(t)$ and $X_\omega(t)$ are the operations and weather processes

$X(t)$ is the product of $X_o(t)$ times $X_\omega/u(t)$

Figure 16. Relationship between blast noise and weather effects.

Mean Value of X(t)

The definition of the mean μ of a stochastic process $X(t)$ is its expected value:

$$\mu_X = E(X(t)) \qquad \text{[Eq 22]}$$

Here the process $X(t)$ is the product of the operations and weather time series so that

$$E(X(t)) = E(X_O(t) \cdot X_W(t)) \qquad \text{[Eq 23]}$$

Since $X_O(t)$ and $X_W(t)$ are independent processes, the expected value of their product becomes the product of the expected values:

$$\mu_X = E(X_O(t)X_W(t)) = E(X_O(t))E(X_W(t)) \qquad \text{[Eq 24]}$$

These expected values are by definition the means of the operations and weather processes:

$$\mu_X = M_O M_W \qquad \text{[Eq 25]}$$

Autocovariance of X(t)

The definition of the autocovariance function, $\gamma_X(\tau)$, of a stationary stochastic process is

$$\gamma_X(\tau) = E(X(t)X(t+\tau)) = E(X_O(t)X_O(t+\tau)X_W(t)X_W(t+\tau) \qquad \text{[Eq 26]}$$

Again, since $X_O(t)$ and $X_W(t)$ are independent processes, the expected values may be separated:

$$\gamma_X(\tau) = E(X_O(t)X_O(t+\tau))E(X_W(t)X_W(t+\tau)) \qquad \text{[Eq 27]}$$

These expected values are by definition the autocovariance functions of the operations and weather processes:

$$\gamma_X(\tau) = \gamma_{X_O}(\tau)\ \gamma_{X_W}(\tau) \qquad \text{[Eq 28]}$$

Sample Mean Variance of X(t)

For the multiplicative model, the sample mean variance may be expressed as

$$\mathrm{VAR}(\overline{X}) = \frac{1}{N} \sum_{\tau=-\infty}^{\infty} \gamma_X(\tau) = \frac{1}{N} \sum_{\tau=-\infty}^{\infty} \gamma_{X_0}(\tau)\, \gamma_{X_W}(\tau) \qquad \text{[Eq 29]}$$

As shown in Chapter 2, the autocovariance function of a stationary stochastic process can be expressed as a function of the parameters of an ARMA model and takes the form of a sum of weighted exponential functions. For the AR(1) weather model, the autocovariance function takes the form

$$\gamma_{X_W}(\tau) = d_W(\phi_W)^\tau \qquad \text{[Eq 30]}$$

where ϕ_W = the autoregressive parameter.

$$d_W = \frac{\sigma_W^2}{1-\phi_W^2} \qquad \text{[Eq 31]}$$

For the Fort Bragg data, the order of the model varied from site to site, but a general autocovariance function can be written which applies to all sites:

$$\gamma_{X_0}(\tau) = \sum_{i=1}^{n} d_i(\lambda_i)^\tau \qquad \text{[Eq 32]}$$

where n = order of the model

λ_i = the ith pole of the model

d_i = the ith autocovariance coefficient.

The variance of the sample mean can then be written as

$$\mathrm{VAR}(\overline{X}) = \frac{1}{N} \sum_{\tau=-\infty}^{\infty} [d_W(\phi_W)^\tau] \left[\sum_{i=1}^{n} d_i(\lambda_i)^\tau\right] \qquad \text{[Eq 33]}$$

Let $d_i' = d_i d_w$ and $\lambda_i' = \lambda_i' \phi_\omega$.

Then

$$VAR(\bar{X}) = \frac{1}{N} \sum_{\tau=-\infty}^{\infty} \sum_{i=1}^{n} d_i' (\lambda_i')^\tau$$

[Eq 34]

Exploiting the symmetry of the autocovariance function, i.e.,
$\gamma(\tau) = \gamma(\tau)$,

$$VAR(\bar{X}) = \left[\frac{1}{N} \sum_{i=1}^{n} d_i' + 2 \sum_{\tau=1}^{\infty} \sum_{i=1}^{n} d_i' (\lambda_i')^\tau\right] \quad \text{[Eq 35]}$$

Interchanging the order of the summations,

$$\sum_{\tau=1}^{\infty} \sum_{i=1}^{n} d_i' (\lambda_i')^\tau = \sum_{i=1}^{n} d_i' \sum_{\tau=1}^{\infty} (\lambda_i')^\tau \quad \text{[Eq 36]}$$

Recalling that $\sum_{p=1}^{\infty} z^p = \frac{z}{1-z}$ $|z| < 1$ for z real or complex,

$$VAR(\bar{X}) = \frac{1}{N} \left[\sum_{i=1}^{n} d_i' + 2 \sum_{i=1}^{n} d_i' \left(\frac{\lambda_i'}{1-\lambda_i'}\right)\right] \quad \text{[Eq 37]}$$

This equation is used to compute the variance of the sample mean given the necessary input parameters regarding the blast operations and weather models. The correlation factor of X(t) is expressed as

$$CF = \left[\sum_{i=1}^{n} d_i' + 2 \sum_{i=1}^{n} d_i' \left(\frac{\lambda_i'}{1-\lambda_i'}\right)\right] \Big/ \left[\sum_{i=1}^{n} d_i'\right] \quad \text{[Eq 38]}$$

The coefficient of variation of X(t) is expressed as

$$CV = \sqrt{\sum_{i=1}^{n} d_i'} \Big/ \mu_X \quad \text{[Eq 39]}$$

In summary, the information required to derive sampling requirements includes:

1. σ_O^2 and σ_W^2, the variances of the white noise processes $a_O(t)$ and $a_W(t)$

2. μ_O and μ_W, the means of operations and weather processes

3. The parameters of the time series models for the blast operations and weather.

All of this information, with the exception of the μ_W and σ_W^2, is available from the time series analysis summarized in Chapters 3 and 4.

Identification of Mean and White Noise Variance for Weather Models

Since time series models developed from airport data are used to characterize weather effects, special attention is necessary to ensure that these models are scaled properly for weather effects. The parameters of the time series models characterize the autocorrelation structure in the data and therefore are independent of the scale of the data. The weather effects should not change the mean value of the blast noise, so Eq 25, the weather model, should have a mean value of 1 energy unit or 0 dB. This corresponds to dividing the airport noise data by its mean value in energy and the white noise variance by the mean squared. Table 11 summarizes values for the weather white noise variance, σ_W^2, from a variety of sites.

Calculation of Sampling Requirements for the Multiplicative Model

To assess the impact of weather effects on the sampling requirements for blast noise, sample calculations for Sites 1, 4, 5, 7, 12, and 13 at Fort Bragg were considered. As noted in Chapter 4, neighboring sites exhibited similar structures; these sites were selected because they were representative of the range of coefficient of variation and correlation factor seen at the installation. Recalling the variation in the weather white noise variance, a range of values are used. Eqs 5 and 37 were used to derive the sample number, N. Tables 12 through 17 summarize the sampling requirements for the multiplicative model at Sites 1, 4, 5, 7, 12, and 13 at Fort Bragg. Trial 1 is the result for the blast operations alone; Trials 2 through 9 are results for the multiplicative model. The weather effects introduce an element of randomness to the blast noise, thus reducing the correlation factor of X(t) compared to the blast noise alone. The level of variation of the weather is reflected in σ_W^2 and influences the coefficient of variation of X(t).

Table 11

Weather White Noise Variances

Site	Weather White Noise Variance σ_w^2
Los Angeles A-1	0.146
Los Angeles L-2	0.142
Los Angeles W-4	0.231
Boston 3A	0.605
Boston 6A	1.08
Boston 9	2.29
Boston 12	0.798
Dulles 1B	0.804
Dulles 6A	2.11
Dulles 8A	0.447
National 15A	0.743
National 20B	0.248
National 21B	0.997

Table 12

Sampling Requirements for Fort Bragg -- Site 1

Trial	ϕ_w	σ_w^2	CV	CF	$N_{0.5\bar{X}}$	% Reduction
1	--	--	2.73	6.85	821	0
2	0.25	0.5	2.02	1.23	81	90
3	0.25	1	2.86	1.23	161	80
4	0.25	2	4.04	1.23	321	61
5	0.25	3	4.95	1.23	481	41
6	0.4	0.5	2.13	1.39	102	88
7	0.4	1	3.02	1.39	204	75
8	0.4	2	4.27	1.39	407	50
9	0.4	3	5.23	1.39	610	26

Table 13

Sampling Requirements for Fort Bragg -- Site 4

Trial	ϕ_w	σ_w^2	CV	CF	$N_{0.5\bar{X}}$	% Reduction
1	--	--	1.65	4.20	1.83	0
2	0.25	0.50	1.22	1.26	31	83
3	0.25	1	1.73	1.26	61	67
4	0.25	2	2.44	1.26	121	34
5	0.25	3	2.99	1.26	181	1
6	0.4	0.5	1.29	1.45	39	79
7	0.4	1	1.82	1.45	78	57
8	0.4	2	2.58	1.45	155	15
9	0.4	3	3.16	1.45	232	-27

Table 14

Sampling Requirements for Fort Bragg -- Site 5

Trial	ϕ_w	σ_w^2	CV	CF	$N_{0.5\bar{X}}$	% Reduction
1	--	--	1.85	7.31	403	0
2	0.25	0.50	1.38	1.26	39	90
3	0.25	1.0	1.95	1.26	77	81
4	0.25	2.0	2.73	1.26	154	62
5	0.25	3.0	3.38	1.26	231	43
6	0.4	0.5	1.46	1.47	50	88
7	0.4	1.0	2.48	1.47	100	75
8	0.4	2.0	3.51	1.47	199	51
9	0.4	3.0	3.57	1.47	298	26

Table 15

Sampling Requirements for Fort Bragg -- Site 7

Trial	$\emptyset_w$	σ_w^2	CV	CF	$N_{0.5\bar{X}}$	% Reduction
1	--	--	1.78	3.79	192	0
2	0.25	0.50	1.30	1.24	34	82
3	0.25	1.00	1.83	1.24	67	65
4	0.25	2.00	2.59	1.24	134	30
5	0.25	3.00	3.18	1.24	200	-4
6	0.40	0.50	1.37	1.41	43	78
7	0.40	1.00	1.94	1.41	85	56
8	0.40	2.00	2.74	1.41	170	11
9	0.40	3.00	3.36	1.41	255	-33

Table 16

Sampling Requirements for Fort Bragg -- Site 12

Trial	$\emptyset_w$	σ_w^2	CV	CF	$N_{0.5\bar{X}}$	% Reduction
1	--	--	1.88	4.24	239	0
2	0.25	0.5	1.39	1.26	39	84
3		1.0	1.96	1.26	78	67
4		2.0	2.78	1.26	155	35
5		3.0	3.40	1.26	233	3
6	0.4	0.5	1.47	1.44	50	79
7		1.0	2.07	1.44	100	58
8		2.0	2.93	1.44	199	17
9		3.0	3.59	1.44	298	-25

Table 17

Sampling Requirements for Fort Bragg -- Site 13

Trial	ϕ_w	σ^2_w	CV	CF	$N_{0.5\bar{X}}$	% Reduction
1	--	--	1.80	2.59	135	0
2	0.25	0.5	1.33	1.15	33	76
3	0.25	1.0	1.88	1.15	66	51
4	0.25	2.0	2.66	1.15	131	3
5	0.25	3.0	3.26	1.15	196	-45
6	0.4	0.5	1.41	1.26	40	70
7	0.4	1.0	1.99	1.26	80	41
8	0.4	2.0	2.81	1.26	160	-19
9	0.4	3.0	3.44	1.26	240	-78

It can be seen that variations in σ_W^2 over the observed range of values have a dramatic influence on the sampling requirements, while the effect of variations in ϕ_W is not as great. As σ_W^2 ranges from 0.50 to 3.00, the sampling requirements are first reduced by as much as 80 percent and then increased by 30 percent. This wide variation suggests the need to carefully consider the σ_W^2 parameter in light of the expected range and distribution of weather effects on blast noise.

Gamma Distribution for Weather Data

Experience suggests that the range of weather effects is 20 to 25 dB with the distribution of values skewed to the right so that a few weather events combine with the blast noise to produce very high sound levels. Figure 17 shows a frequency distribution with these characteristics. The Gamma distribution[7] is a mathematical probability density function capable of quantifying these characteristics and thus provides a means for analytically computing σ_W^2. The form of the Gamma distribution is

$$f(X) = \frac{X^{\alpha-1} \exp(-X/\beta)}{\beta^{\alpha}\,\Gamma(\alpha)} \quad X \geq 0 \qquad \text{[Eq 40]}$$

where X is a random variable in decibel units with the Gamma distribution

$\Gamma(\alpha)$ is the Gamma function evaluated at α

α,β are the parameters of the distribution.

The mean of the Gamma distribution is $(\alpha\beta)$, the mode is $(\alpha-1)\beta$, and the variance is $(\beta^2\alpha)$. Figures 18 through 20 show plots of Gamma distributions with the desired range and skewness characteristics.

It is now necessary to derive the distribution, mean and variance of the random variable Y where

$$Y = 10^{\left(\frac{X}{10}\right)} . \qquad \text{[Eq 41]}$$

Thus Y is a random variable for the weather effects in energy units.

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[7]Norma Johnson and Samuel Kotz, Continuous Univariate Distributions-1, (Houghton Mifflin, 1970).

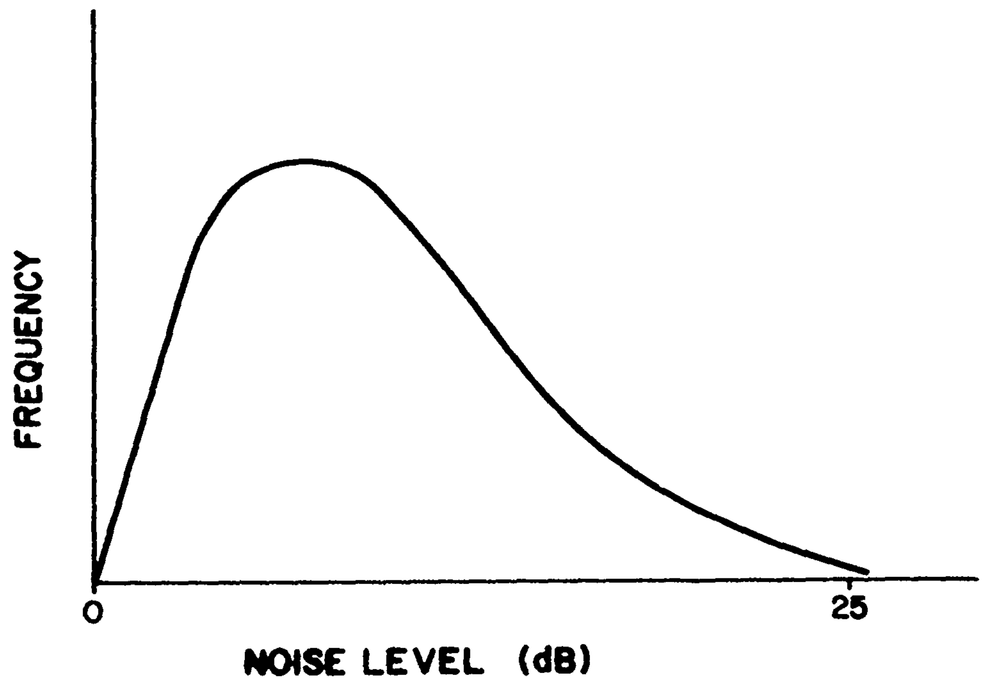

Figure 17. Frequency distribution for weather effects.

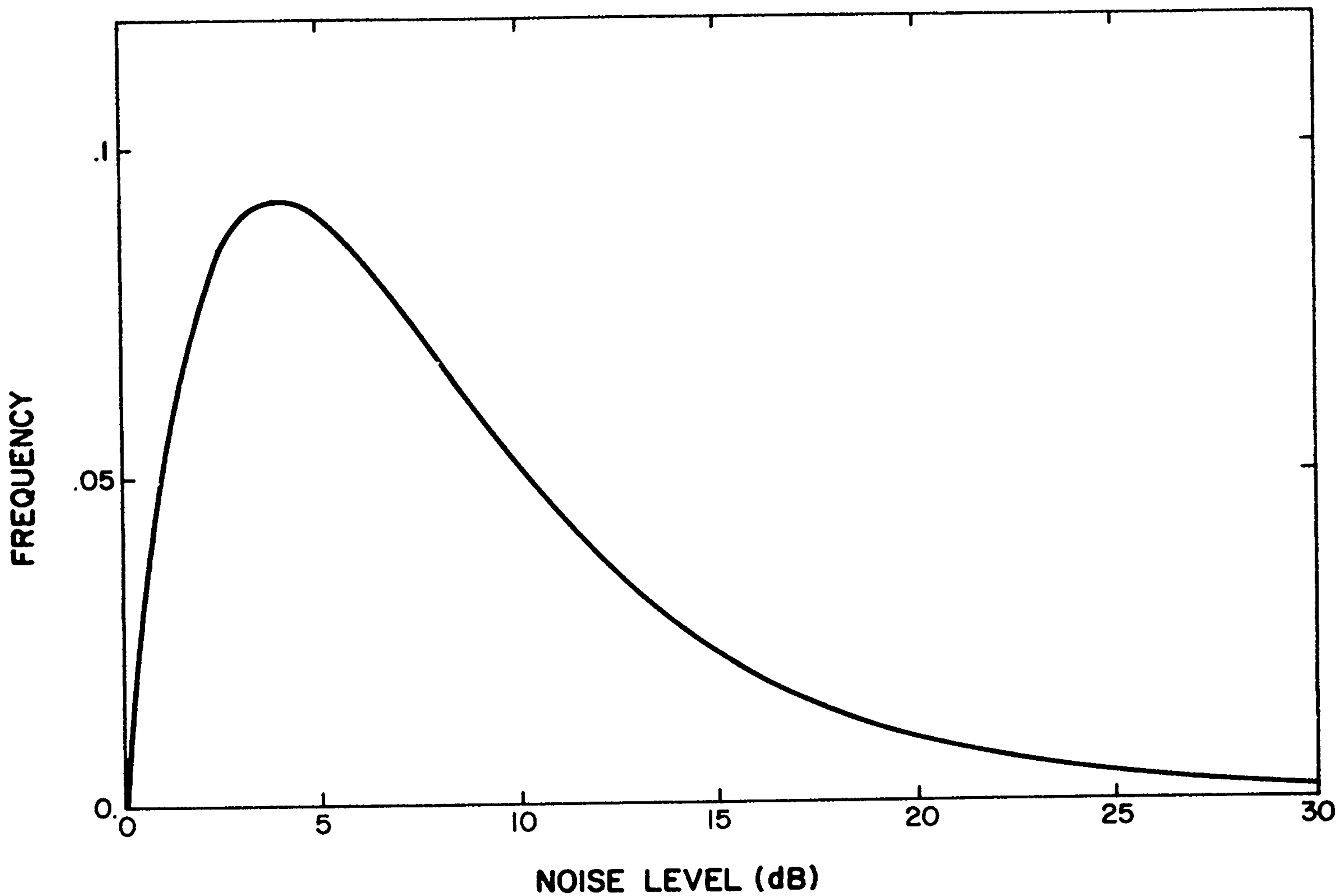

Figure 18. Gamma distribution with $\alpha = 2$, $\beta = 4$.

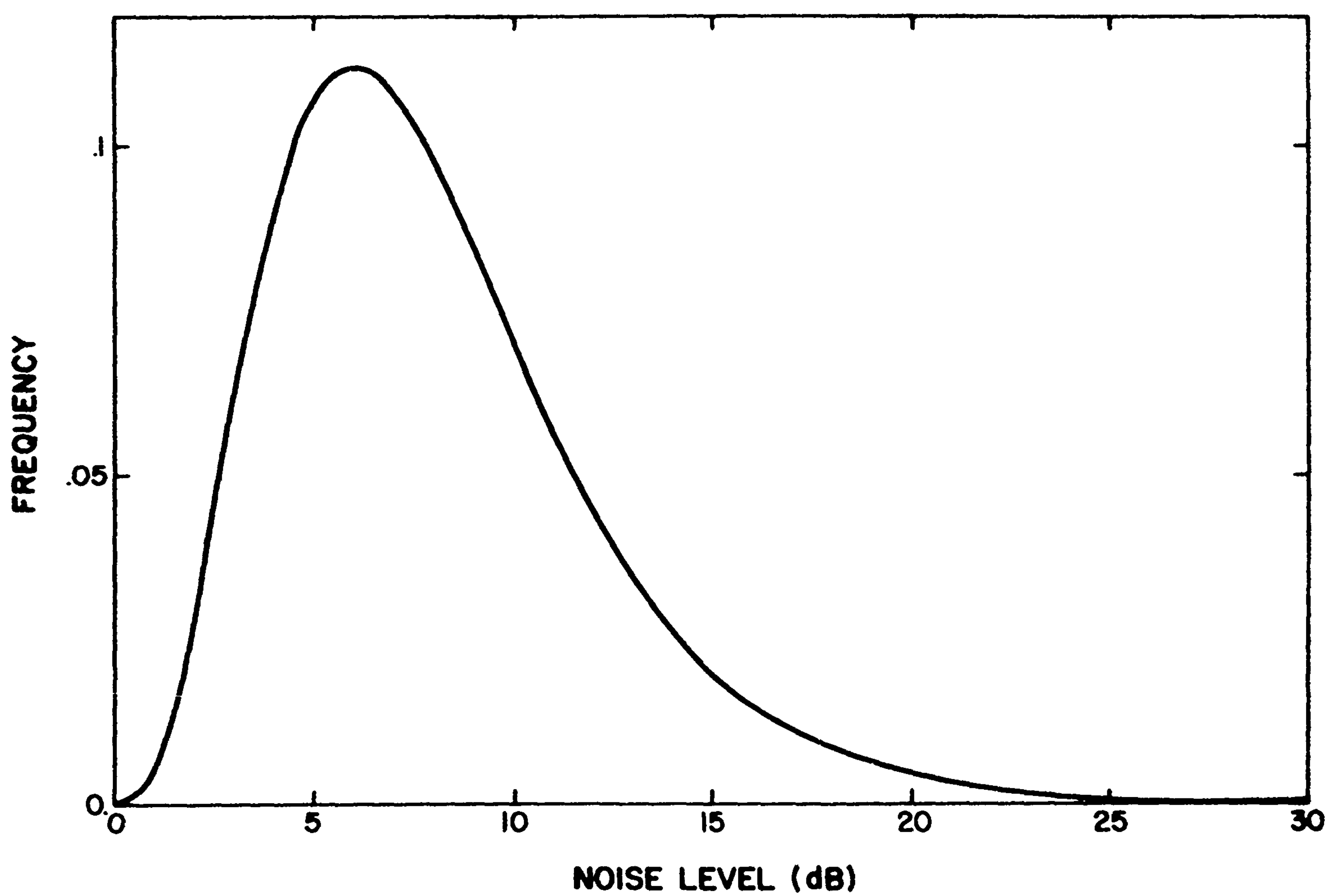

Figure 19. Gamma distribution with $\alpha = 4$, $\beta = 2$.

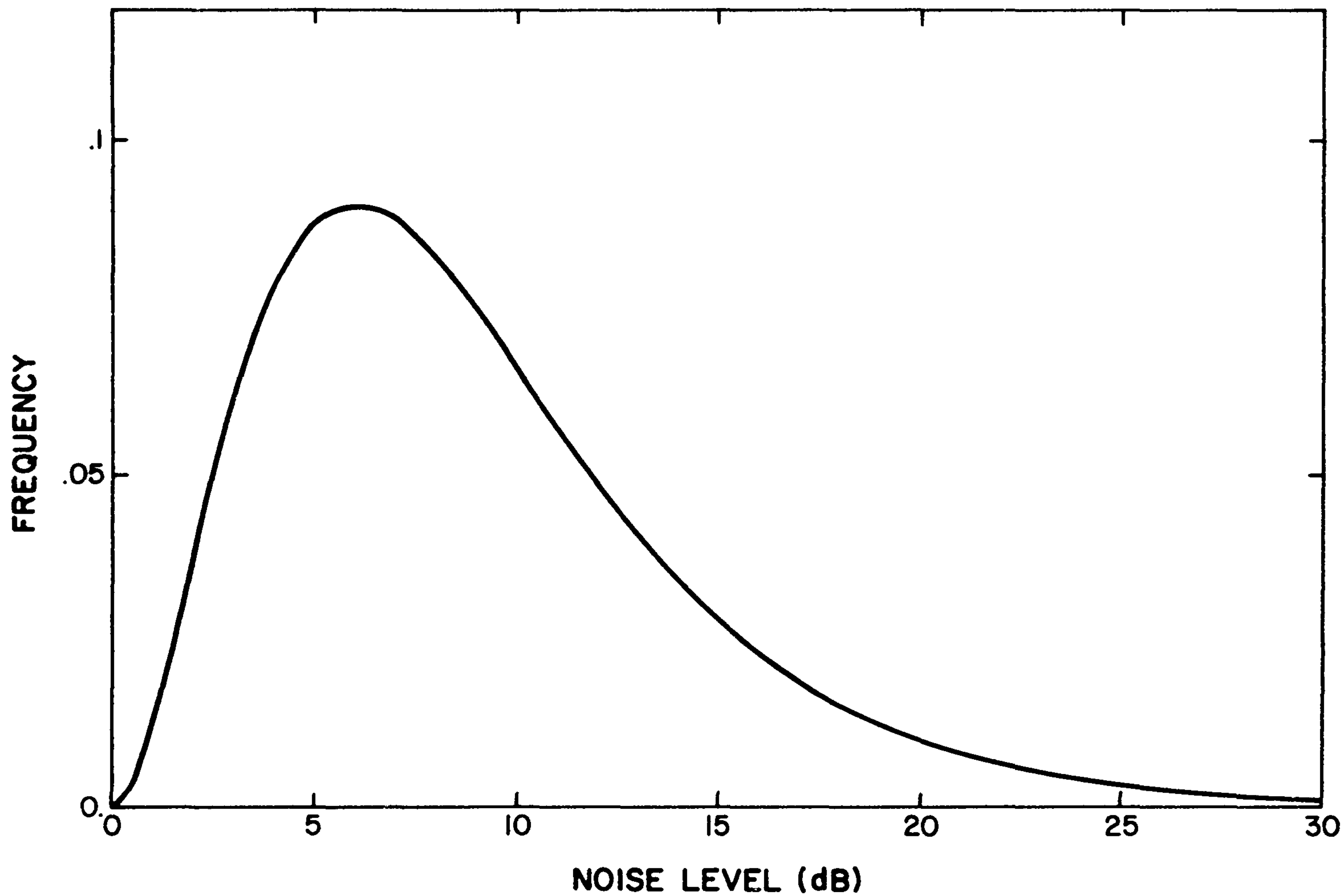

Figure 20. Gamma distribution with = 3, β = 3.

The probability density function of Y is expressed as[8]

$$f(Y) = \frac{f_1(X_1)}{|g'(X_1)|} + \frac{f_2(X_2)}{|g'(X_2)|} + \cdots \frac{f_n(X_n)}{|g'(X_n)|} \qquad \text{[Eq 42]}$$

where X_i is the ith root of g(X)

g(X) is the transformation relating X to Y

$$g'(X) = \frac{dg(X)}{dX}$$

The decibel-to-energy transformation is given by Eq 41, so g(X) has only one root:

$$X = 10 \log_{10} Y \qquad \text{[Eq 43]}$$

The derivative of g(X) is

$$g'(X) = 10^{\frac{X}{10}} (\log_e 10)(\tfrac{1}{10}) = 0.230(10^{\frac{X}{10}}) \qquad \text{[Eq 44]}$$

Substituting Eqs 43 and 44 into Eq 42, the distribution of Y is obtained:

$$f(Y) = \frac{(10 \log_{10} Y^{\alpha-1} \exp(-(10 \log_{10} Y)/\beta)}{(0.230y)\ \beta^{\alpha}\ \Gamma(\alpha)} \qquad \text{[Eq 45]}$$

The definitions of the mean, μ_Y and variance, σ_Y^2 of Y are:

$$\mu(Y) = \int_1^{\infty} Yf(Y)dY \qquad \text{[Eq 46]}$$

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[8] Athanasias Papoulis, Probability, Random Variables, and Stochastic Processes (McGraw-Hill, 1965).

and

$$\sigma_Y^2 = \int_1^{\infty} (Y-\mu_Y)^2 \; f_Y(Y)dY \qquad \text{[Eq 47]}$$

These quantities have been integrated numerically from $1 \leq Y \leq 600$ for these pairs of α and β in Figures 18 through 20 and the results summarized in Table 18. Recalling that there is the mean and variance of the output of the weather process, Eq 30 must be used to solve for the white noise variance σ_W^2 of the weather process. This white noise variance must be divided by the mean, μ_Y, squared. Table 19 summarizes values : the white noise variance. It appears that values of σ_W^2 from 1.5 to 3.0 are representative values.

Table 18

Mean and Variance for Gamma Distributions

α	β	μ_Y	σ_Y^2
2	4	16.90	2087.4
4	2	11.11	533.4
3	3	18.47	1928.2

Table 19

Weather White Noise Variance From Gamma Distribution

α	β	ϕ_W	σ_W^2
2	4	0.25	4.11
2	4	0.40	2.63
4	2	0.25	2.43
4	2	0.40	1.56
3	3	0.25	3.18
3	3	0.40	2.03

6 CONCLUSIONS

In this study, daily average noise data have been examined for the purpose of determining sampling requirements for the precise estimation of long-term (yearly) mean noise levels in the vicinity of airports and military installations. Sampling requirements are assessed by statistically determining the number of consecutive days which must be sampled to estimate the yearly average noise level within ±50 percent of the mean in energy (+2, -3 dB) at the 0.05 significance level.

The stochastic characteristic of serially ordered daily average noise data--i.e., stationary fluctuations about a fixed mean with a constant but autocorrelated pattern of variation--led to the use of DDS as a means to characterize noise time series. ARMA time series models were used to quantify the autocorrelation in the data to provide for the estimation of the variance of the sample mean.

The results of this study have led to the following specific conclusions and recommendations.

General

1. In assessing sampling requirements for the estimation of the yearly average noise level, two statistics sufficiently describe those characteristics which influence the variation in sampling requirements among airports and installations. These are the autocorrelation factor and the coefficient of variation. The autocorrelation factor is a single varied index which is calculated as a function of the estimated parameters of the ARMA model for the noise data. It may be thought of as the multiplier applied to the variance of the sample mean obtained by assuming that the data are uncorrelated and therefore quantifies the degree of autocorrelation in the data. The coefficient of variation is also a single valued index which quantifies the amount of overall variation in the data relative to its mean level.

2. The magnitude of sampling requirements for consecutive sampling has been found to be such that alternate sampling methods should be examined to reduce these requirements. The basic concepts of importance sampling should be examined as a means to develop sampling strategies which give rise to significant reductions in sampling requirements.

At Airports and Community Sites

Noise data from a number of commercial airports, a military airfield, and a military artillery training installation were studied to ascertain sampling requirements for the estimation of yearly average noise levels. In each case, data from monitoring at several locations were examined. While sampling requirements vary as a function of (a) the nature of operations, (b) proximity to those operations, and (c) weather

characteristics indigenous to the area, the general requirements are large, varying from 1 to several months of consecutive sampling. In particular, the following results were obtained.

1. For the commercial airports studied (LAX, Boston Logan, Washington Dulles, and Washington National), the sampling requirements are 30 to 60 days of consecutive sampling.

2. For community noise sites in the vicinity of Washington Dulles, the sampling requirements vary from 15 to 60 days of consecutive sampling.

At Army Installation Site

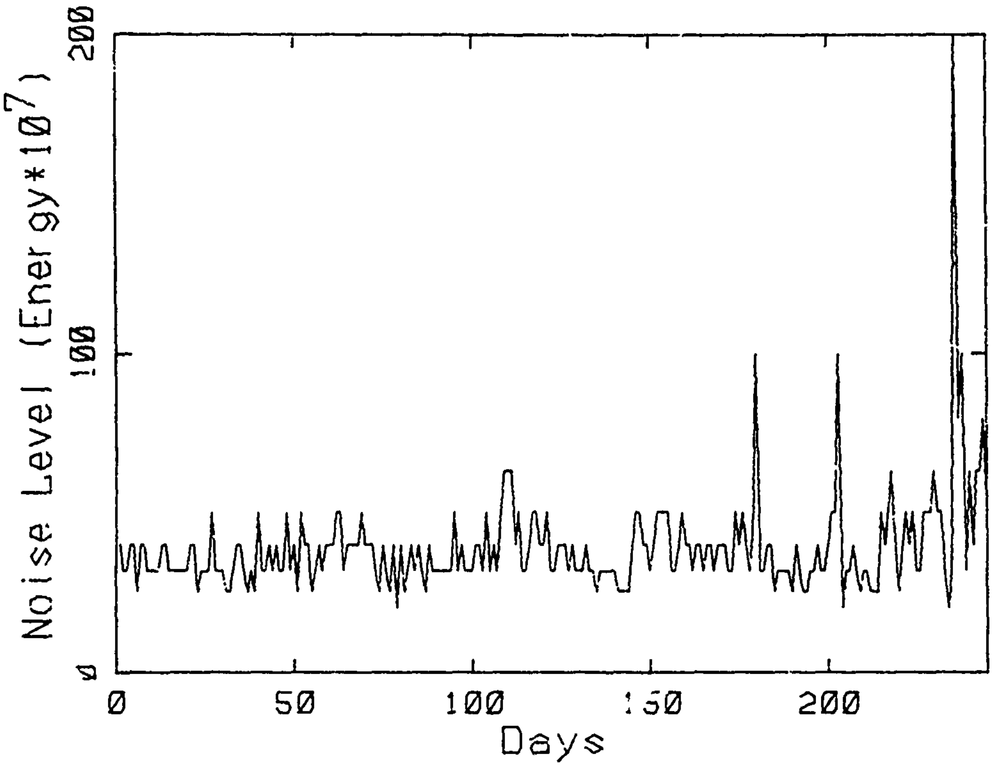
1. Noise data monitored in the vicinity of military installations such as Fort Bragg are characterized by infrequent but high-level blast noise modulated by the effects of weather. For Fort Bragg, ARMA models were developed for data obtained by a computer program which predicts noise as a function of operations and long-term average weather conditions. To account for the day-to-day variations in weather, approximate weather models were defined by selecting certain models representing noise data at LAX. As a first approximation, it was assumed that such models could represent the autocorrelated structure attributable primarily to weather variations because of the consistency of operations at LAX. These approximate weather models are first-order autoregressive models with the autoregressive parameter between 0.25 and 0.50. A combined multiplicative operations and weather model was proposed and used to obtain sampling requirements for various locations about Fort Bragg.

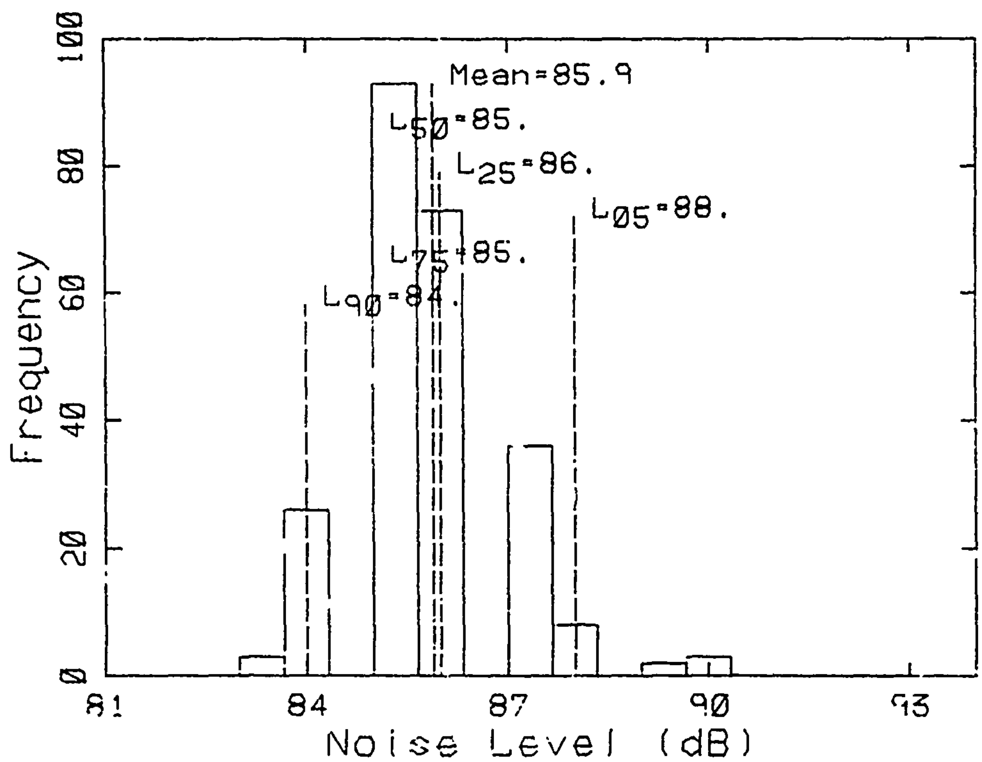
2. For Fort Bragg, the sampling requirements vary from at least 50 to 150 days of consecutive sampling.

3. The proposed combined weather and operations model for Fort Bragg must be viewed as tentative. Actual data from various monitoring sites needs to be collected and modeled to verify the use of an AR(1) model to represent the influence of weather on operations noise data. Modeling a time series obtained by dividing daily average actual data by daily average computer-predicted data should give some indication as to the appropriateness of the multiplicative form of the combined model and the AR(1) form for the weather model.

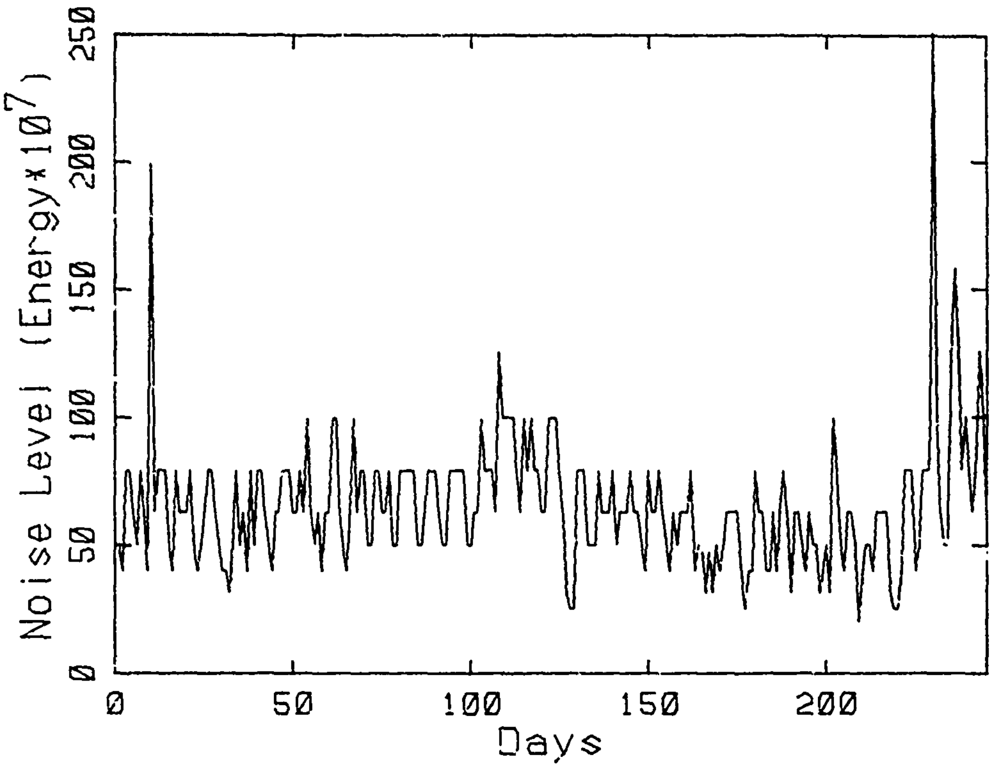
APPENDIX A:

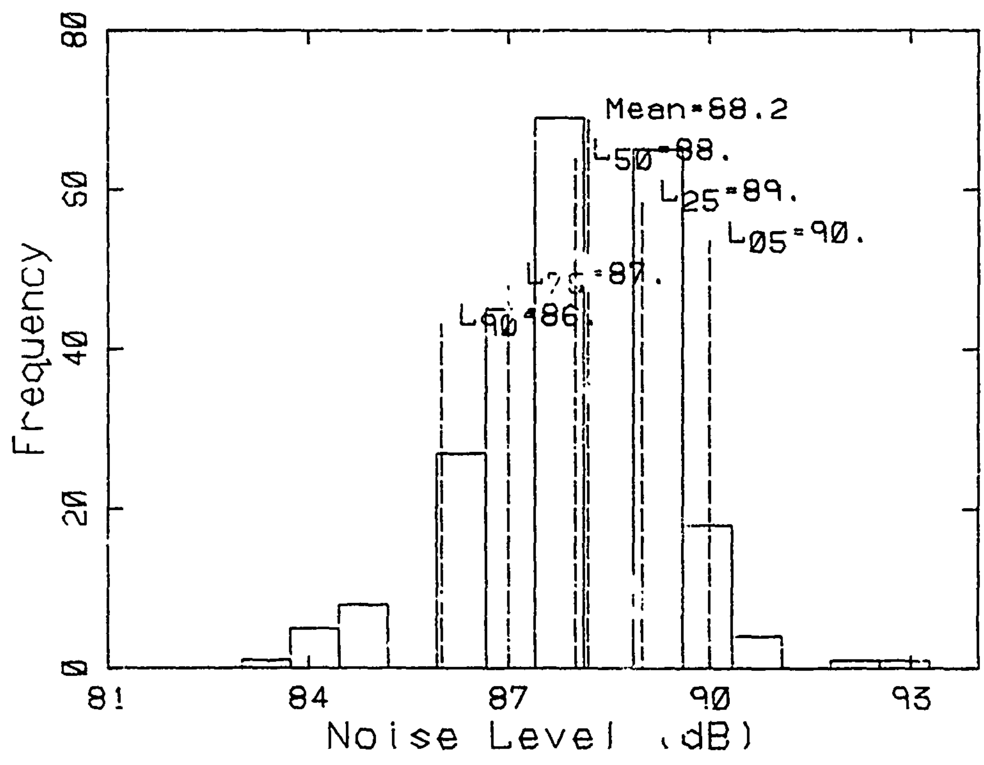
LOS ANGELES INTERNATIONAL AIRPORT HISTOGRAMS AND TIME SERIES PLOTS



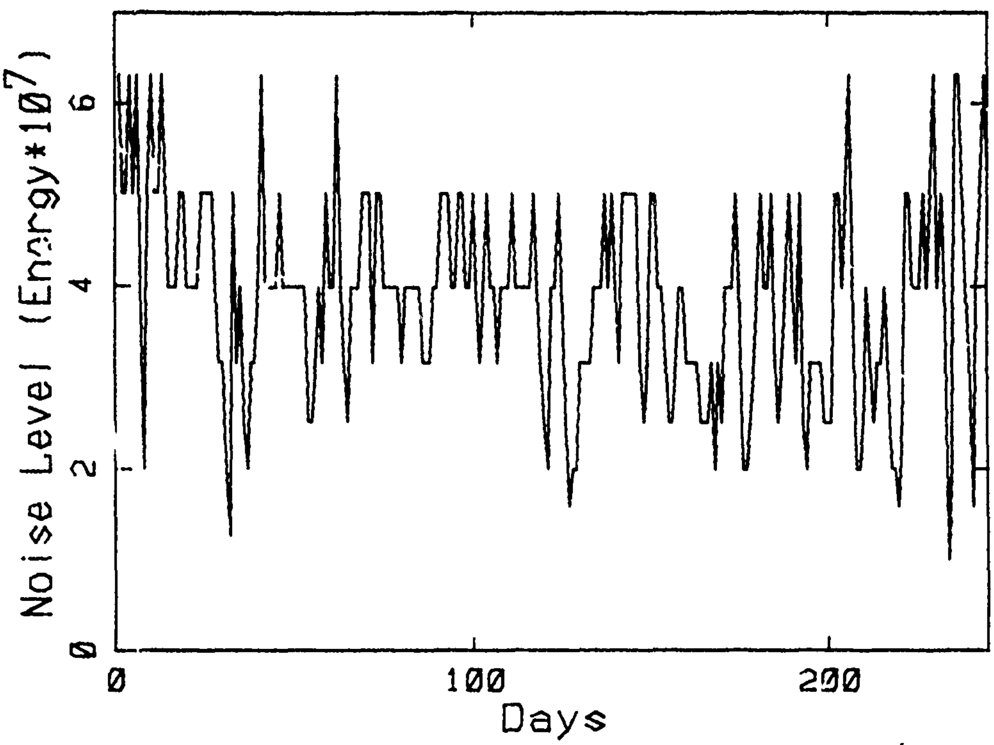


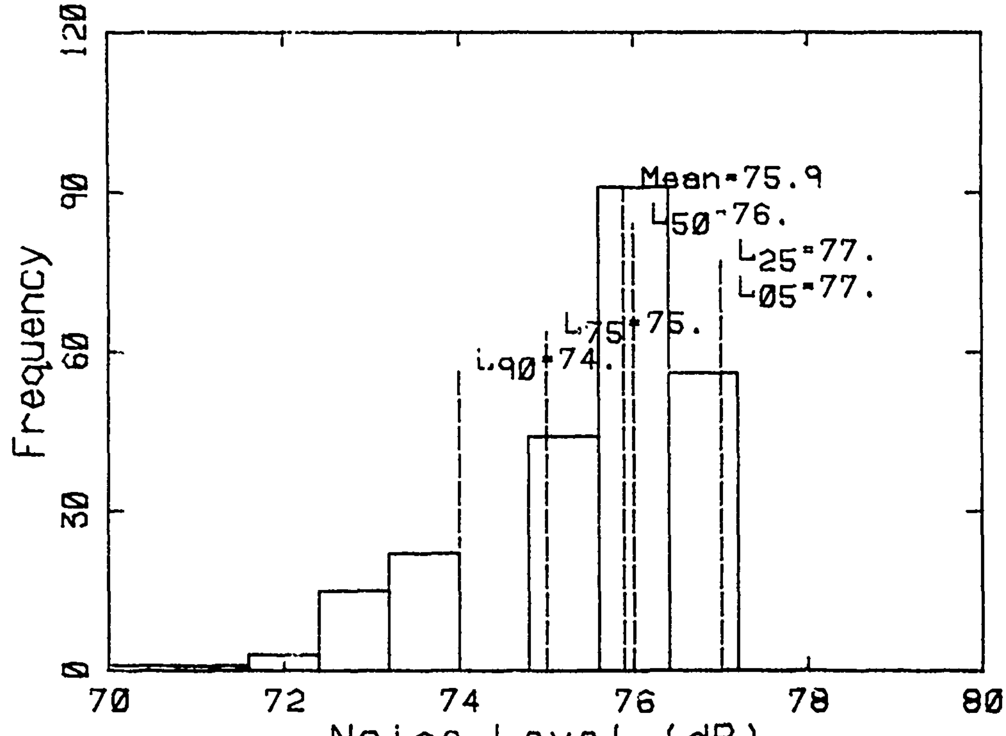
Los Angeles Site A1





Los Angeles Site A2





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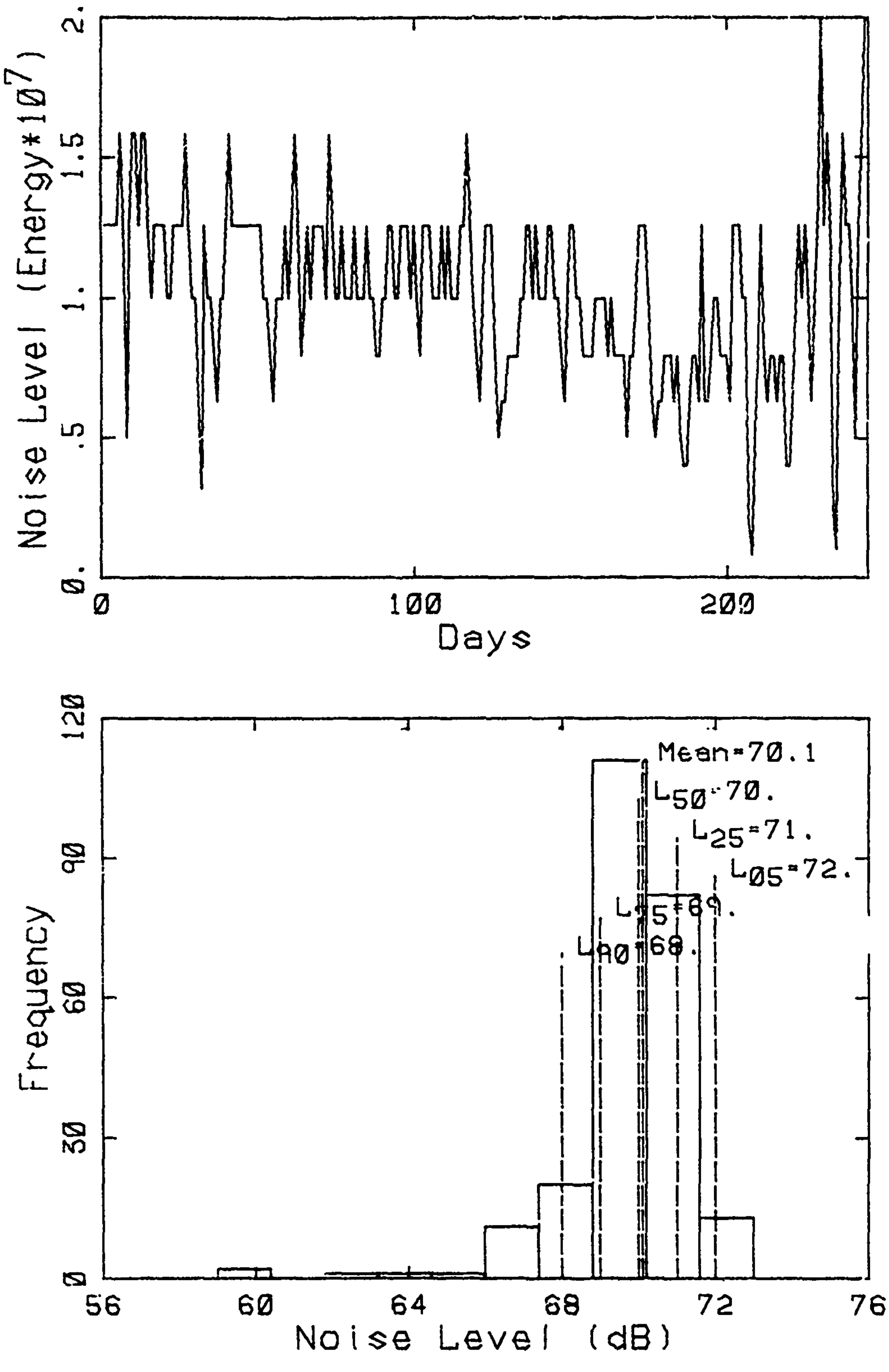

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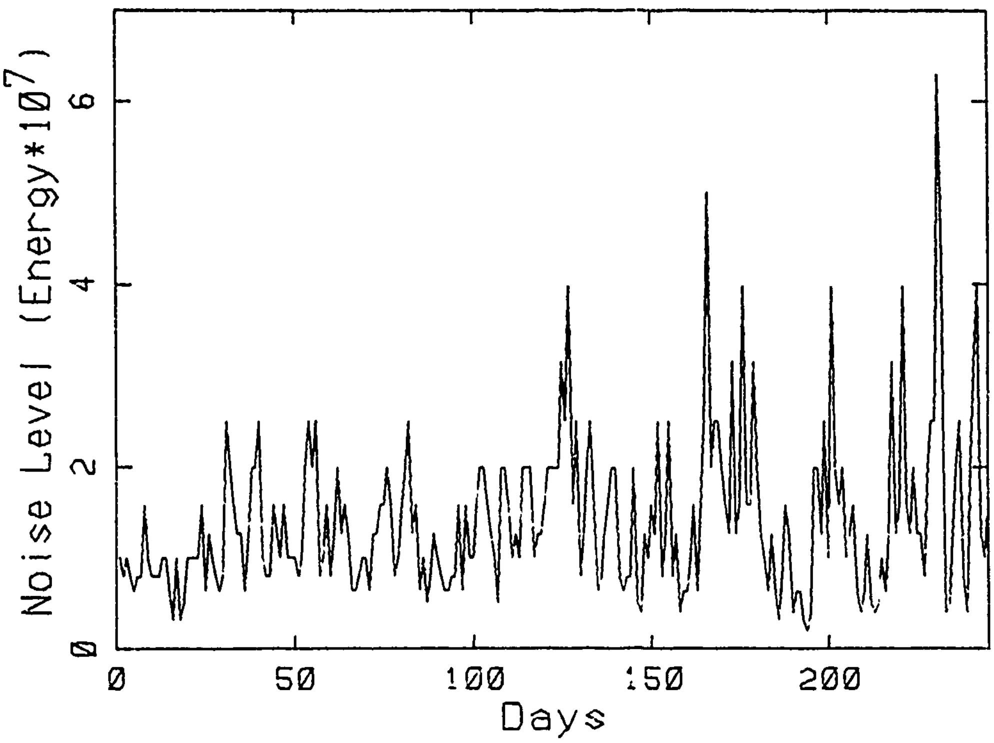

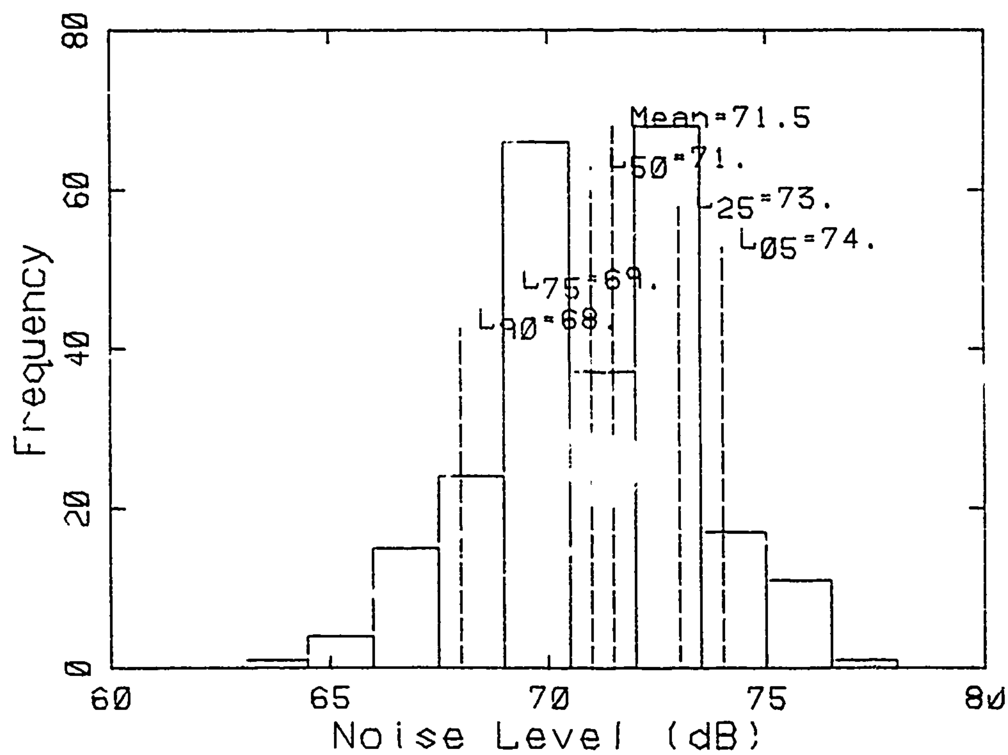

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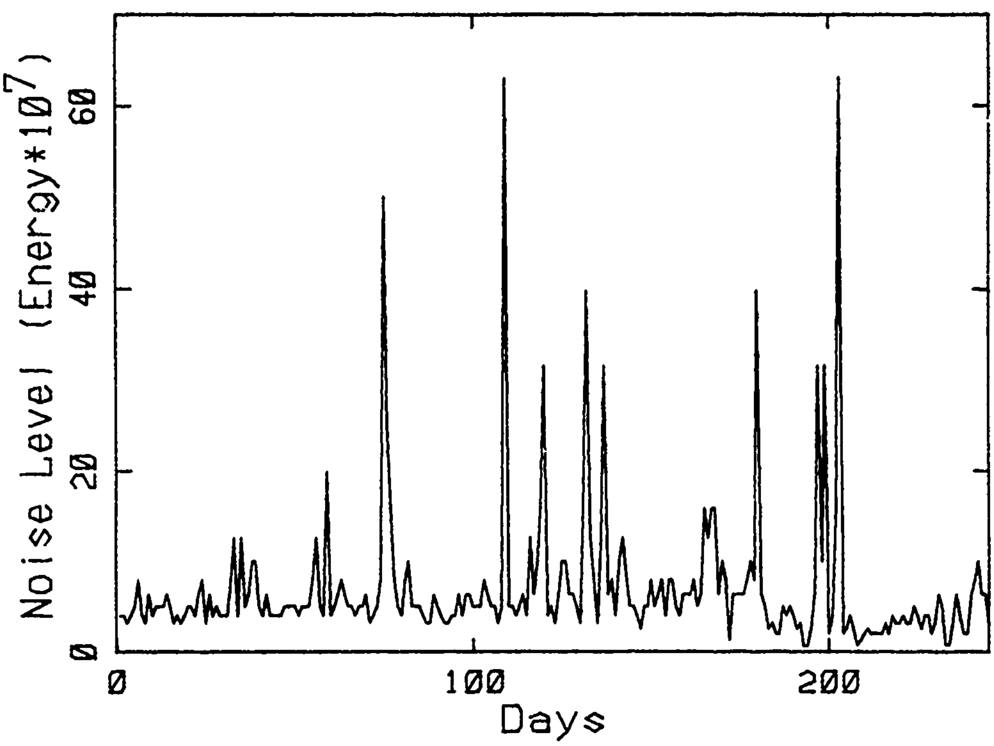

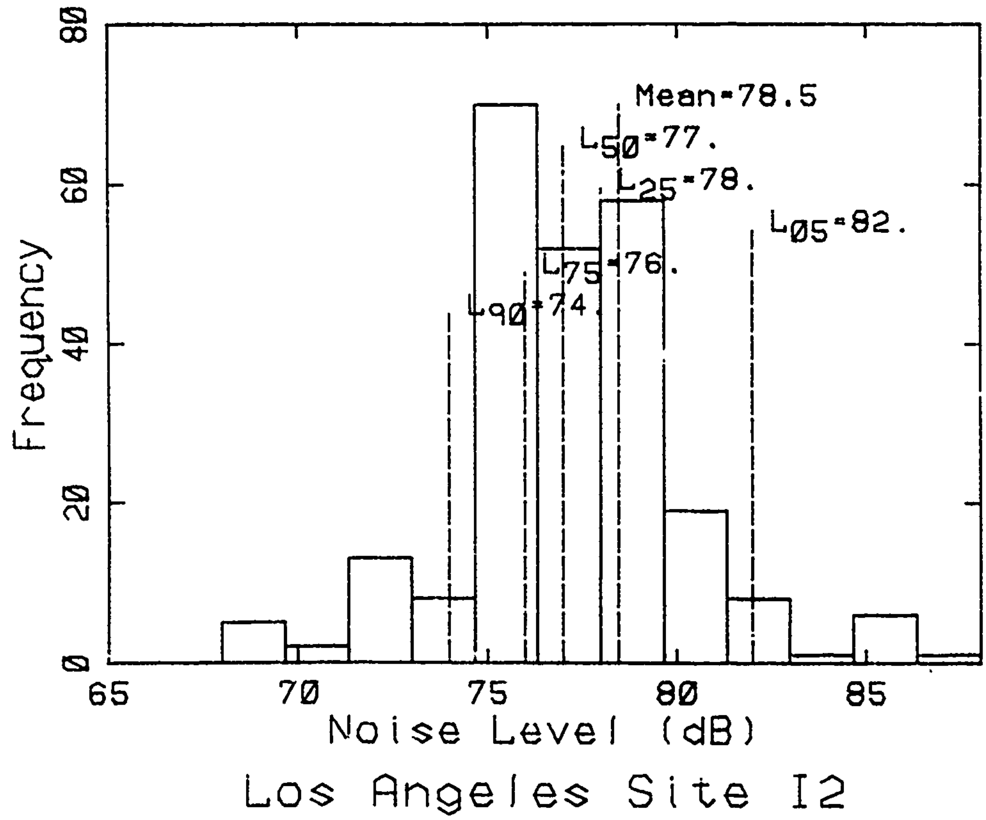

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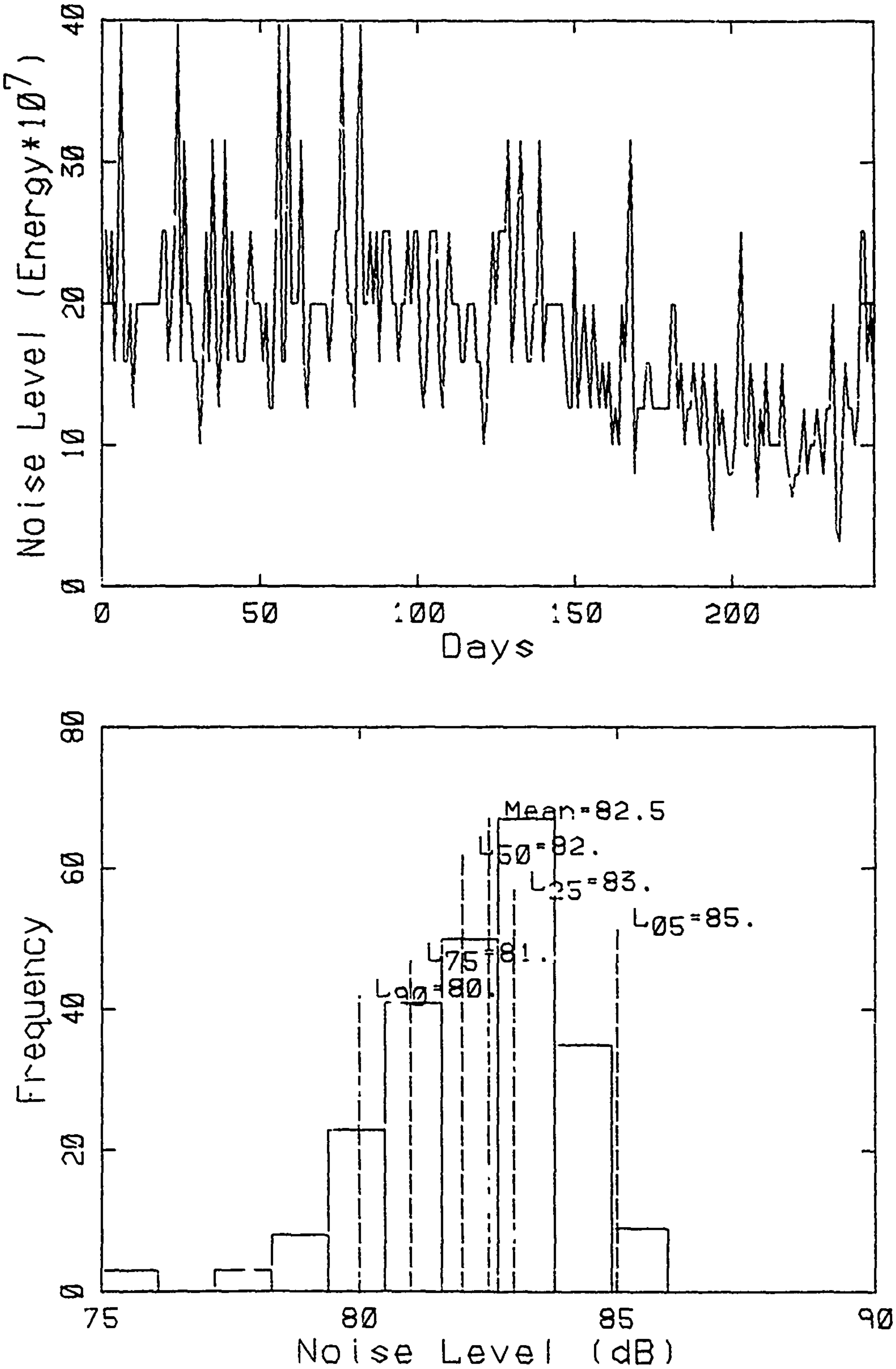

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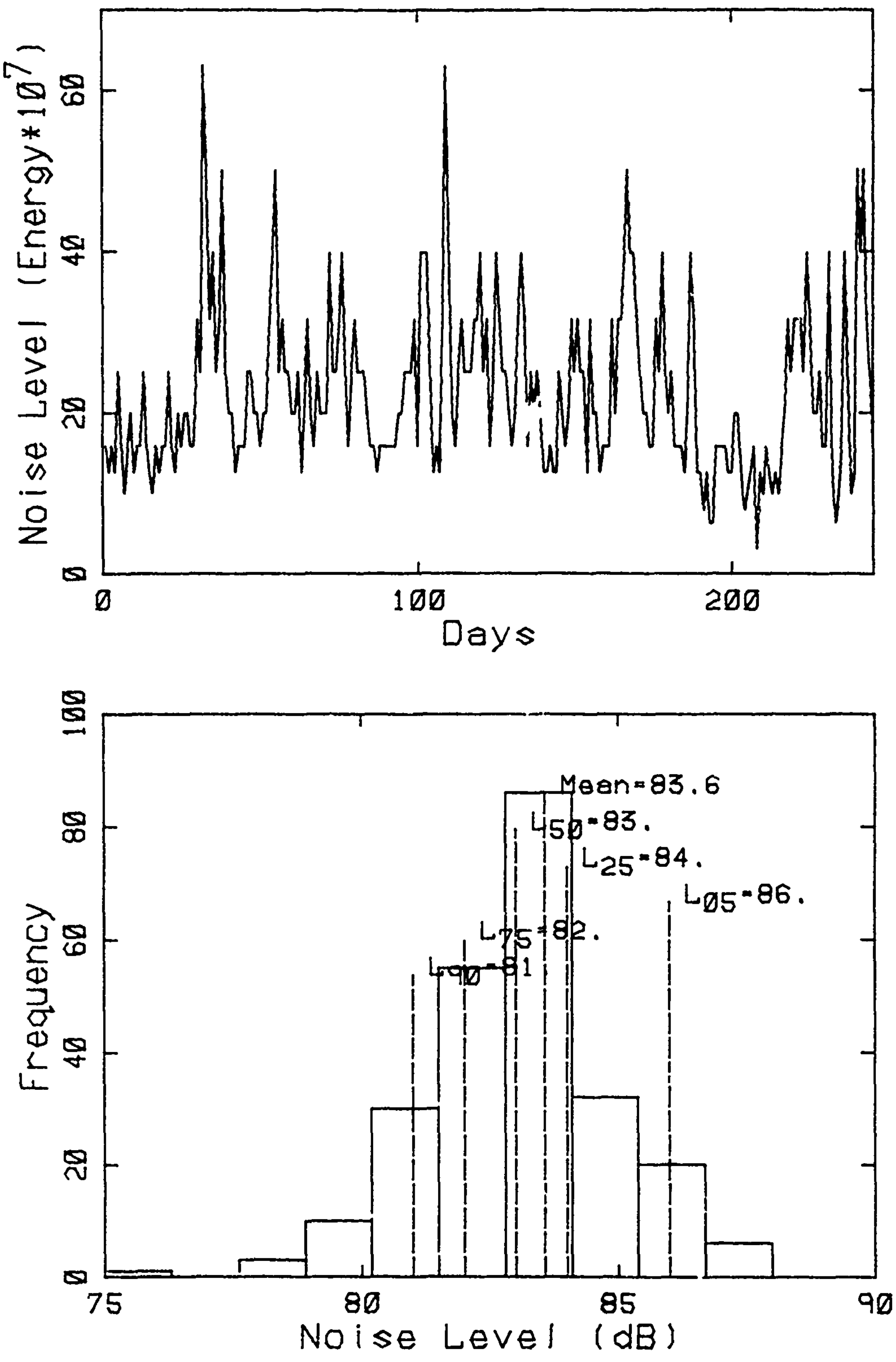

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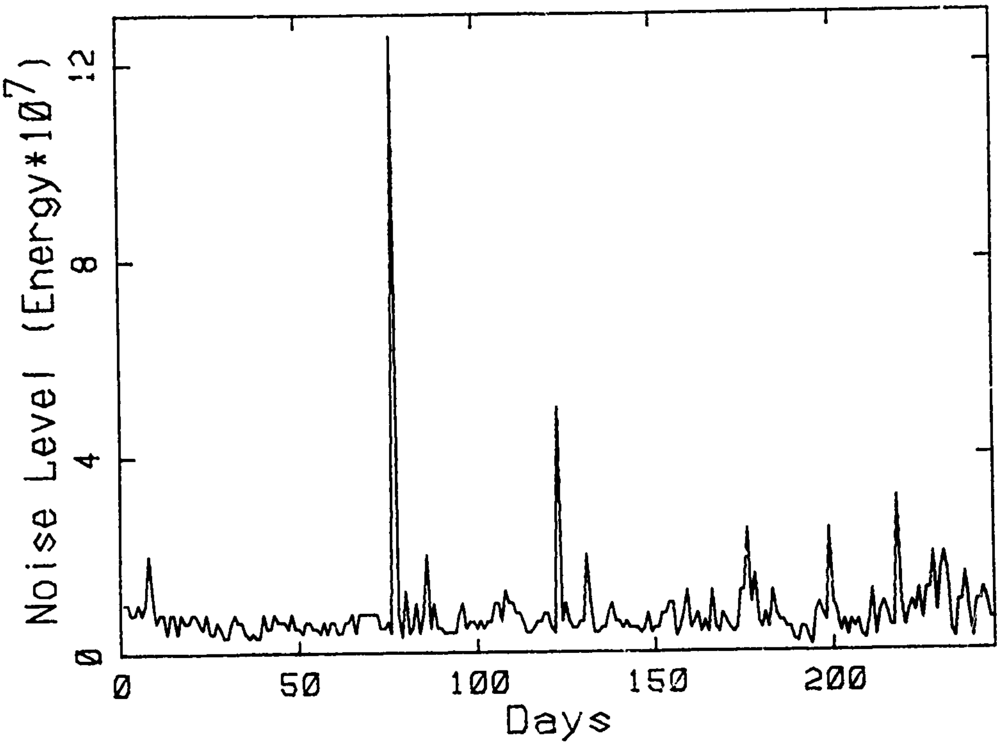

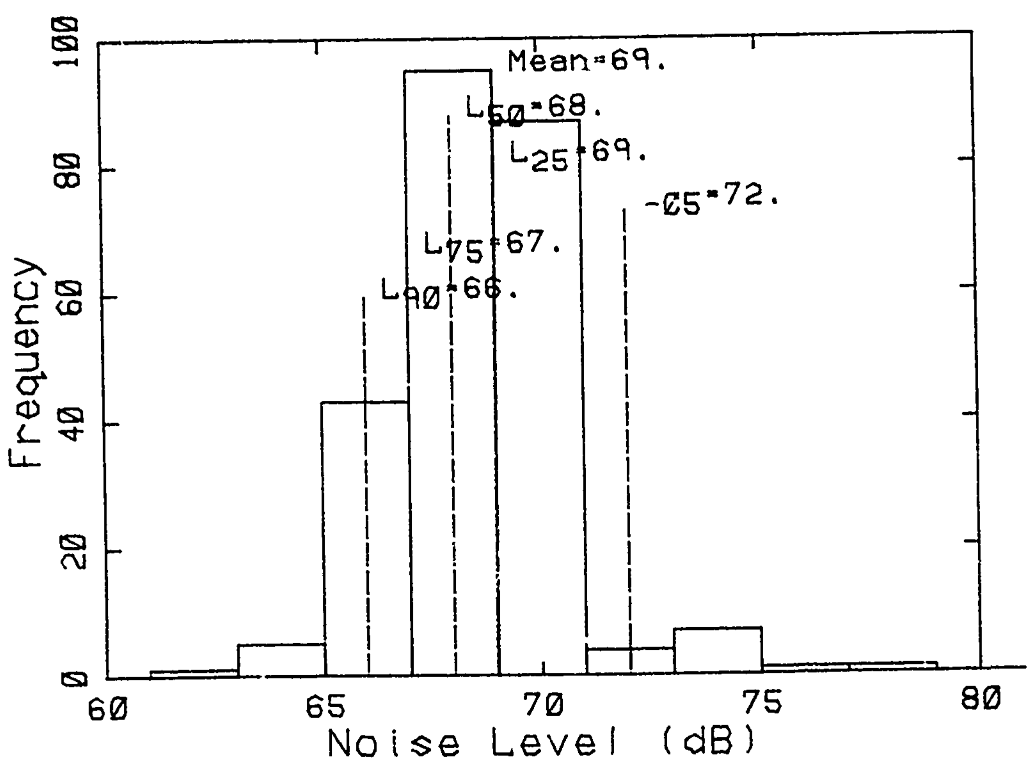

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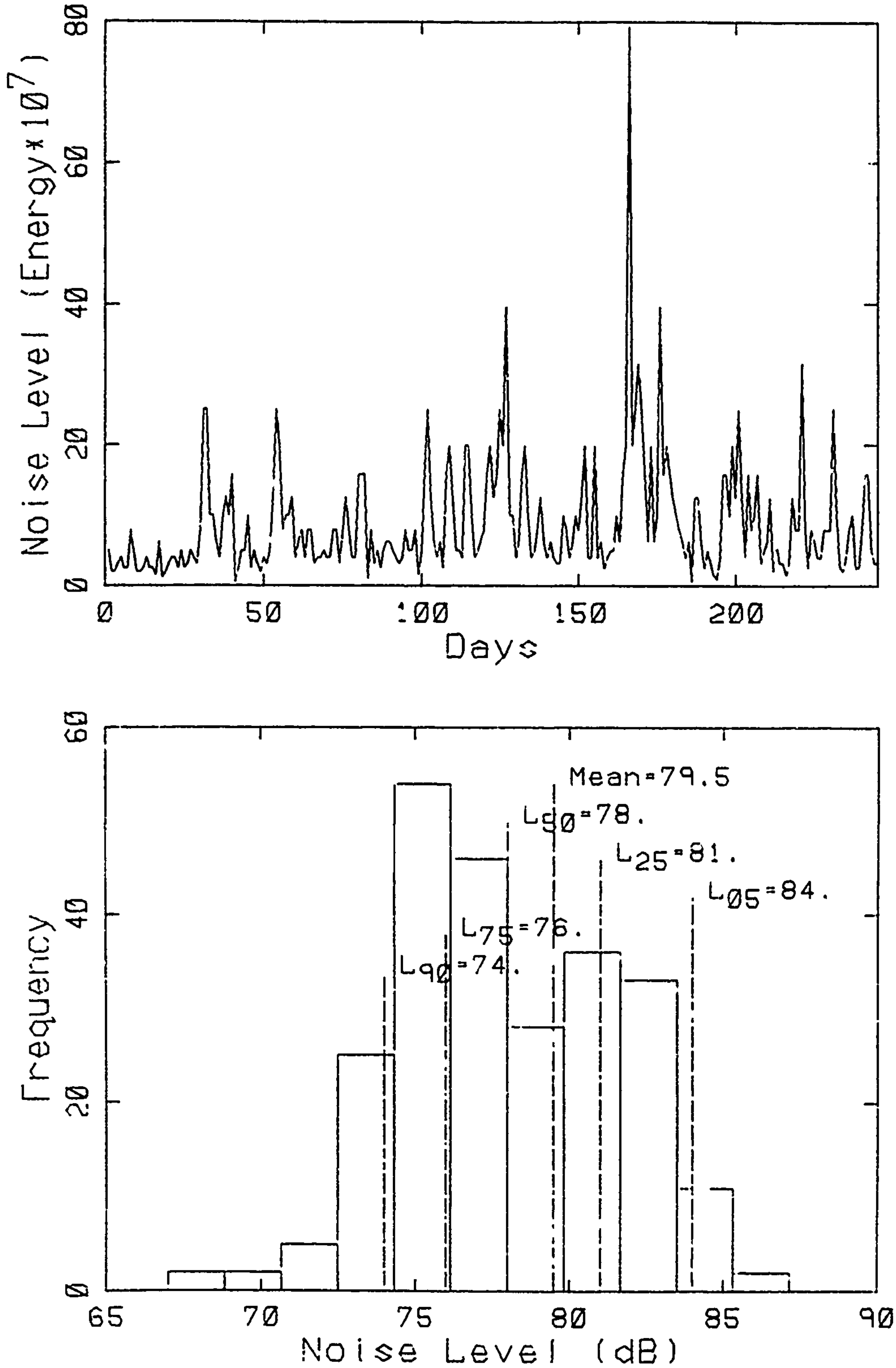

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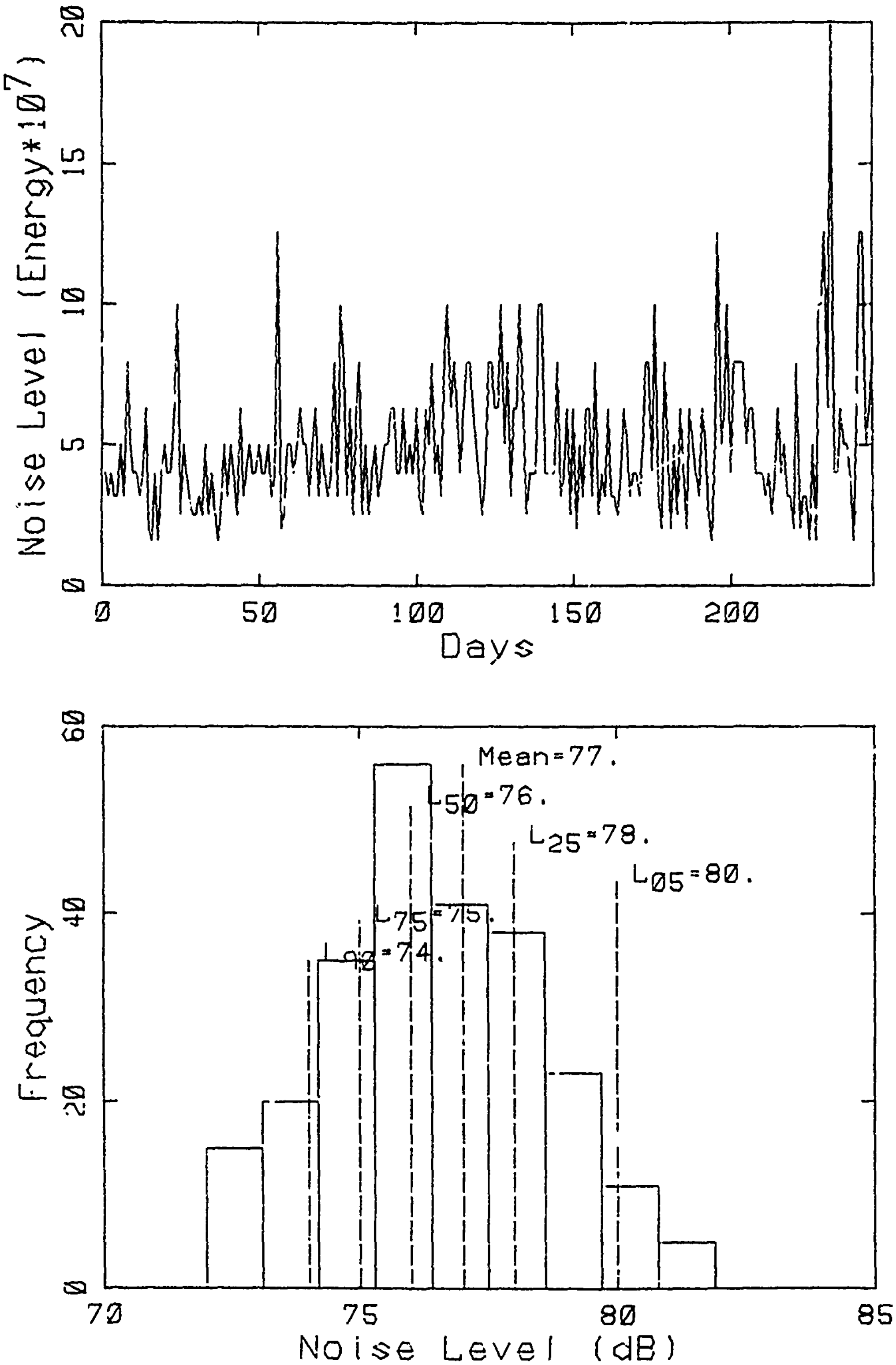
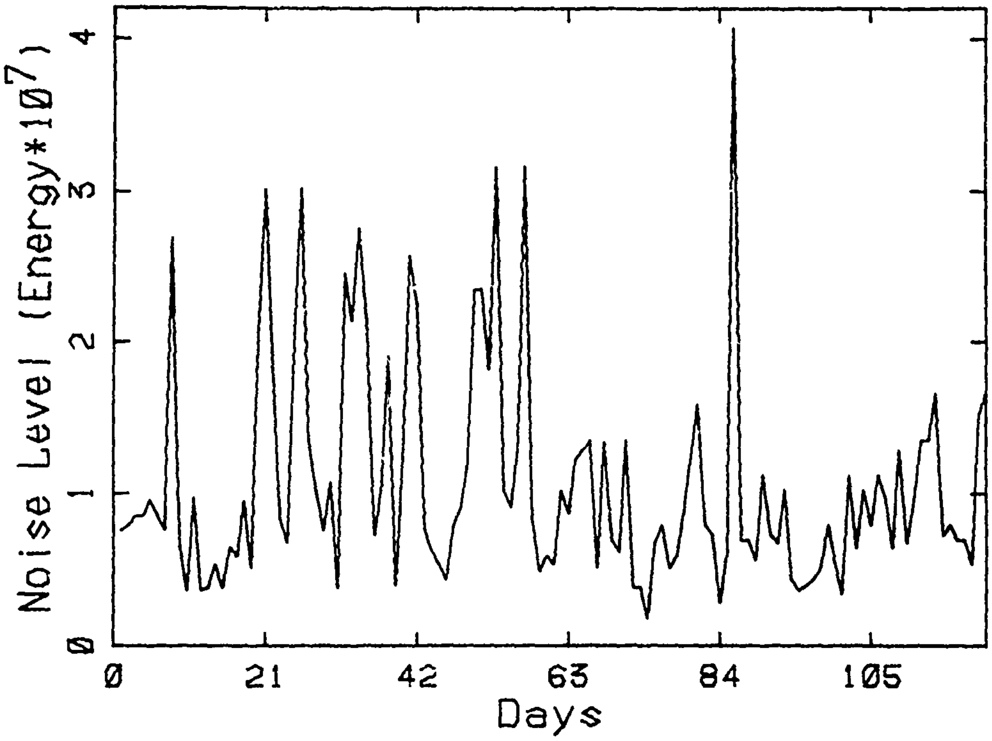
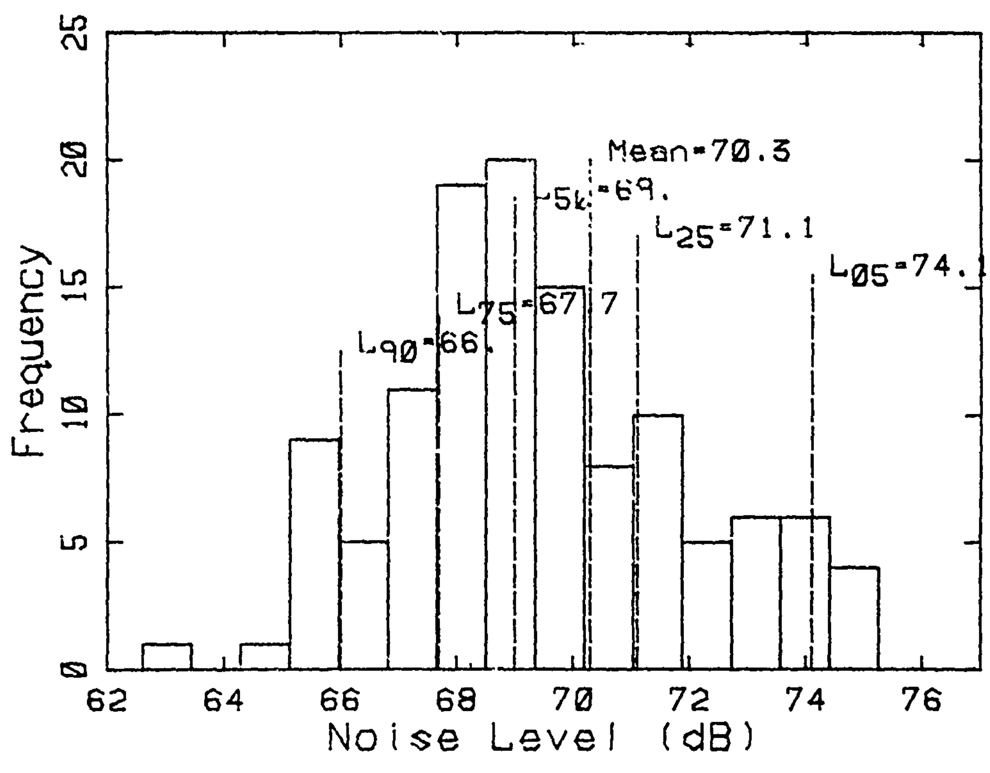


Los Angeles Site W4

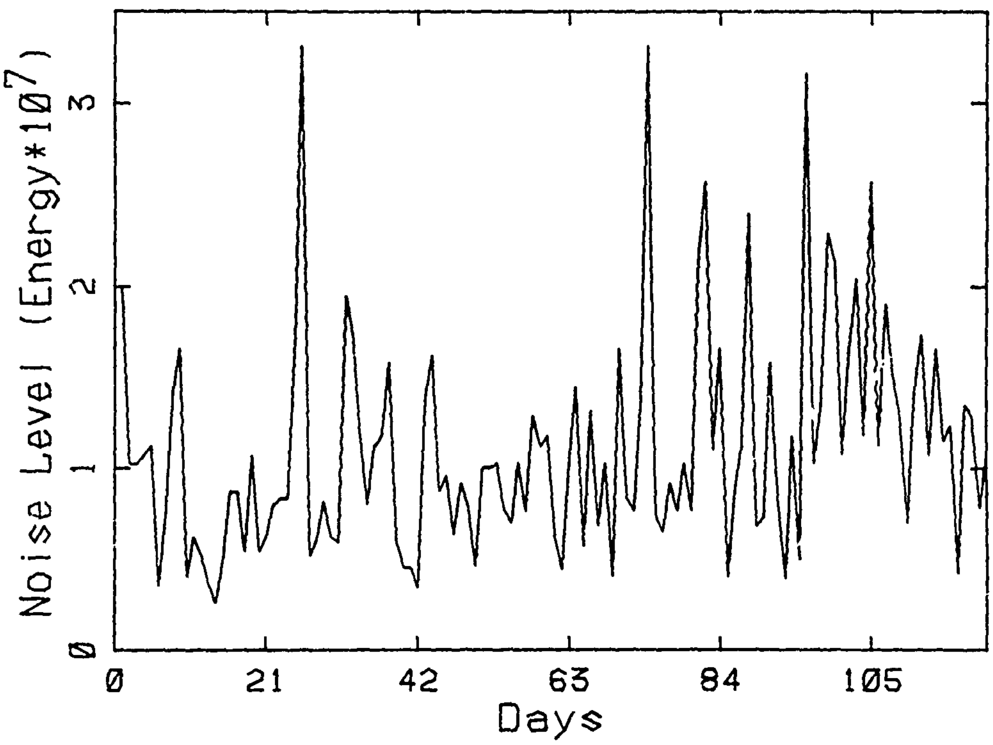
APPENDIX B:

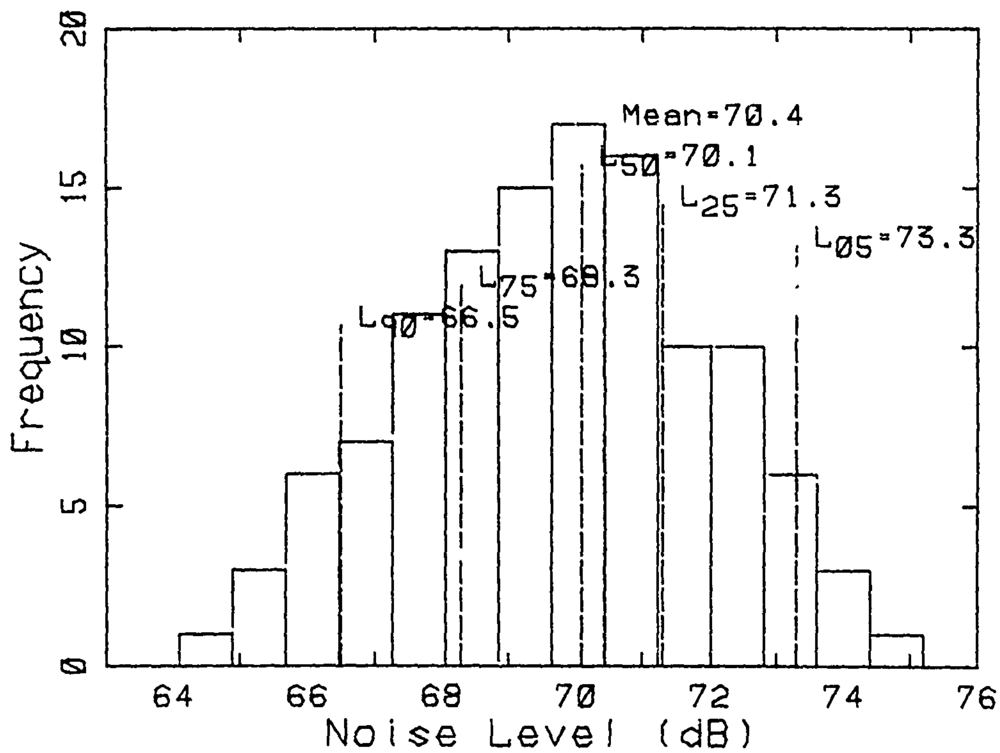
BOSTON LOGAN AIRPORT HISTOGRAMS AND TIME SERIES PLOTS



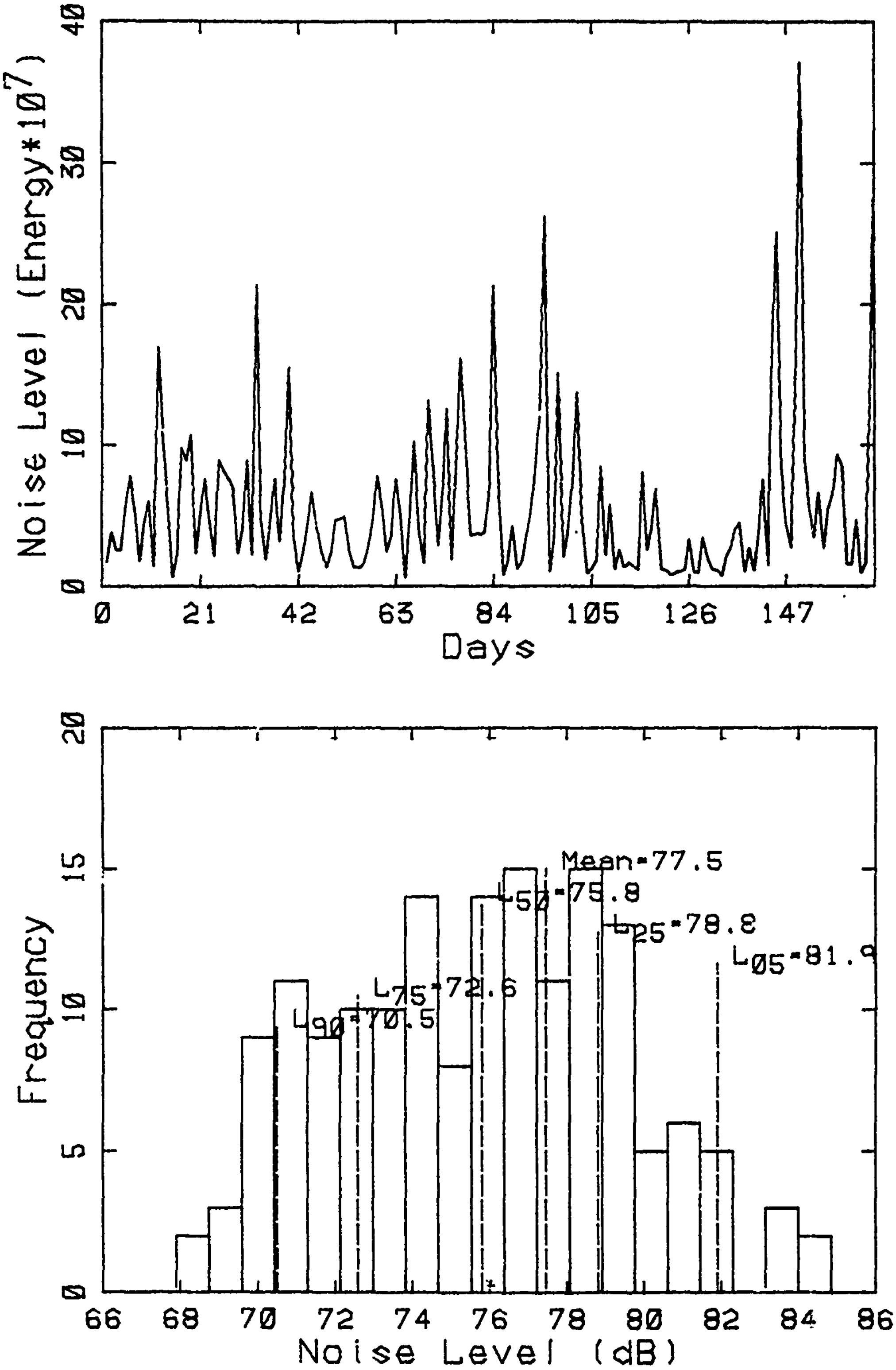


Boston Logan Site 1A

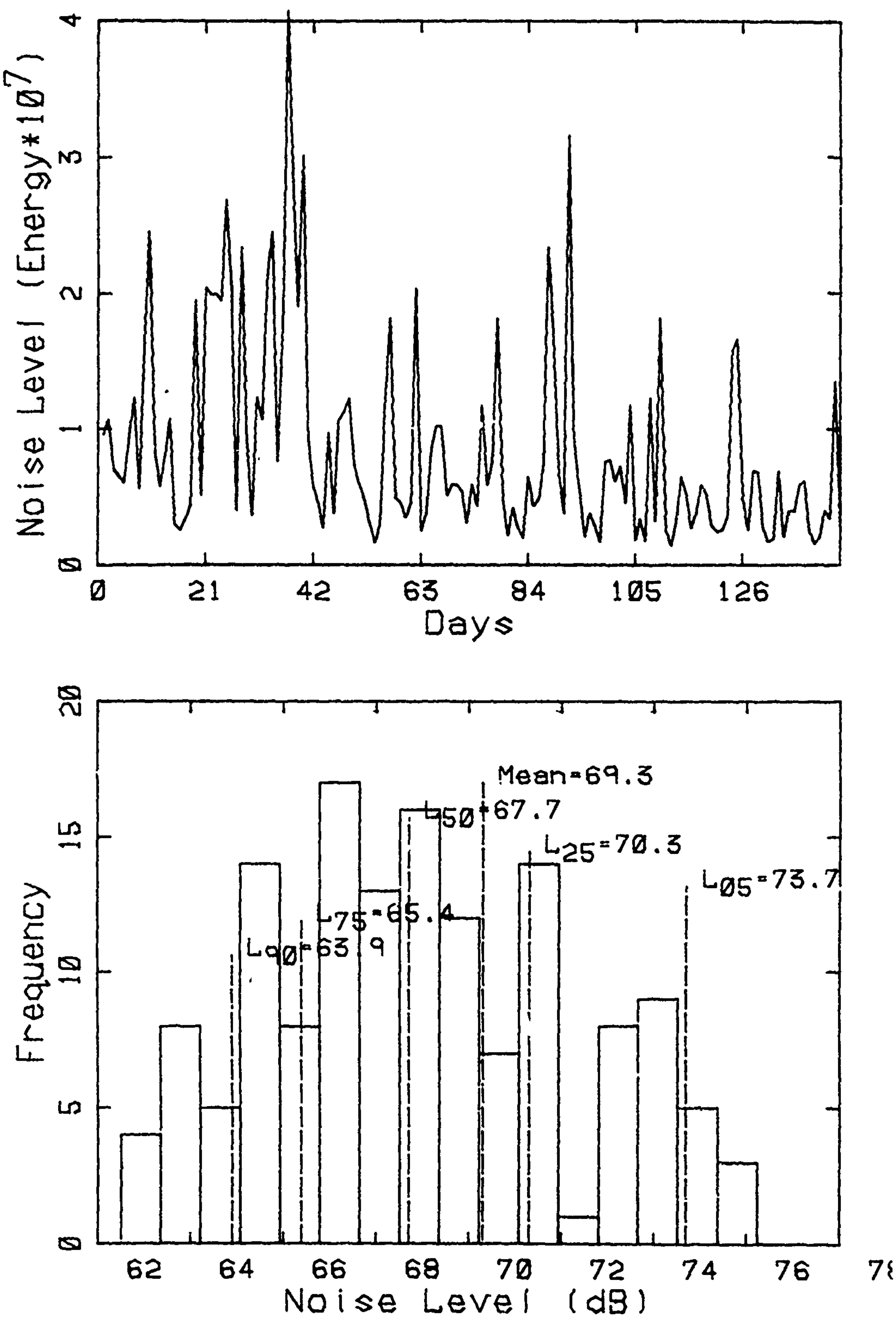




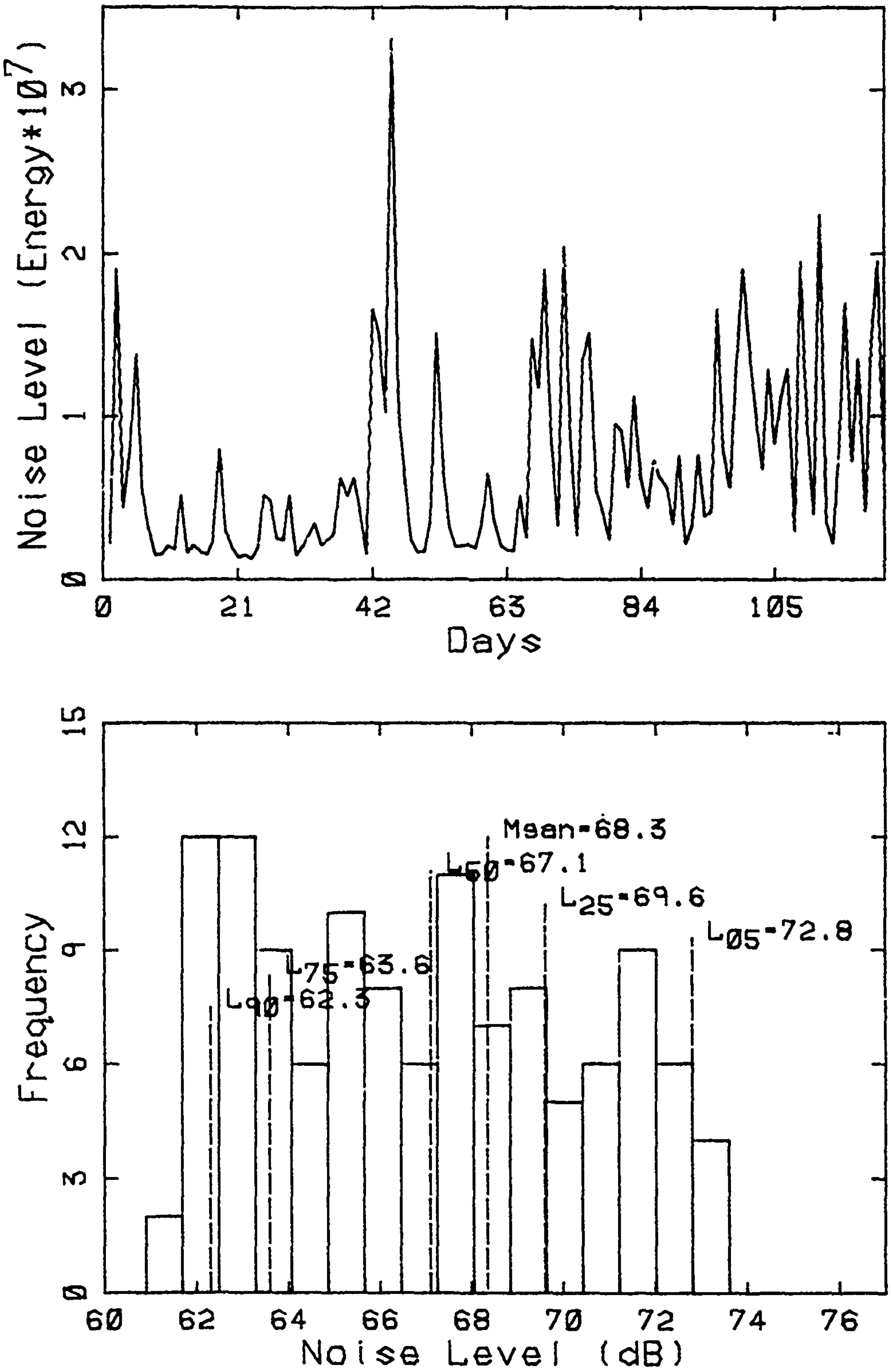
Boston Logan Site 1B



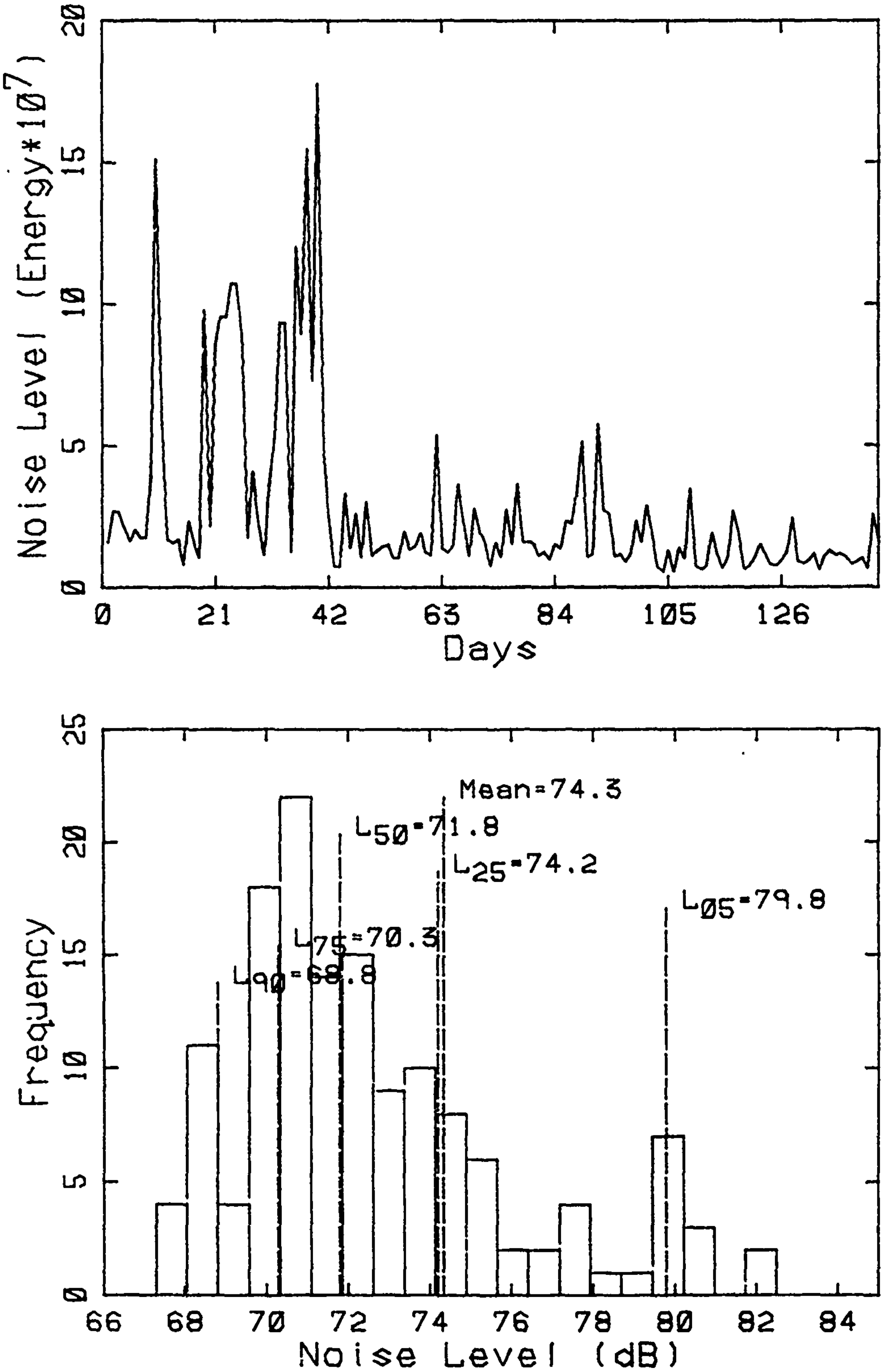
Boston Logan Site 2



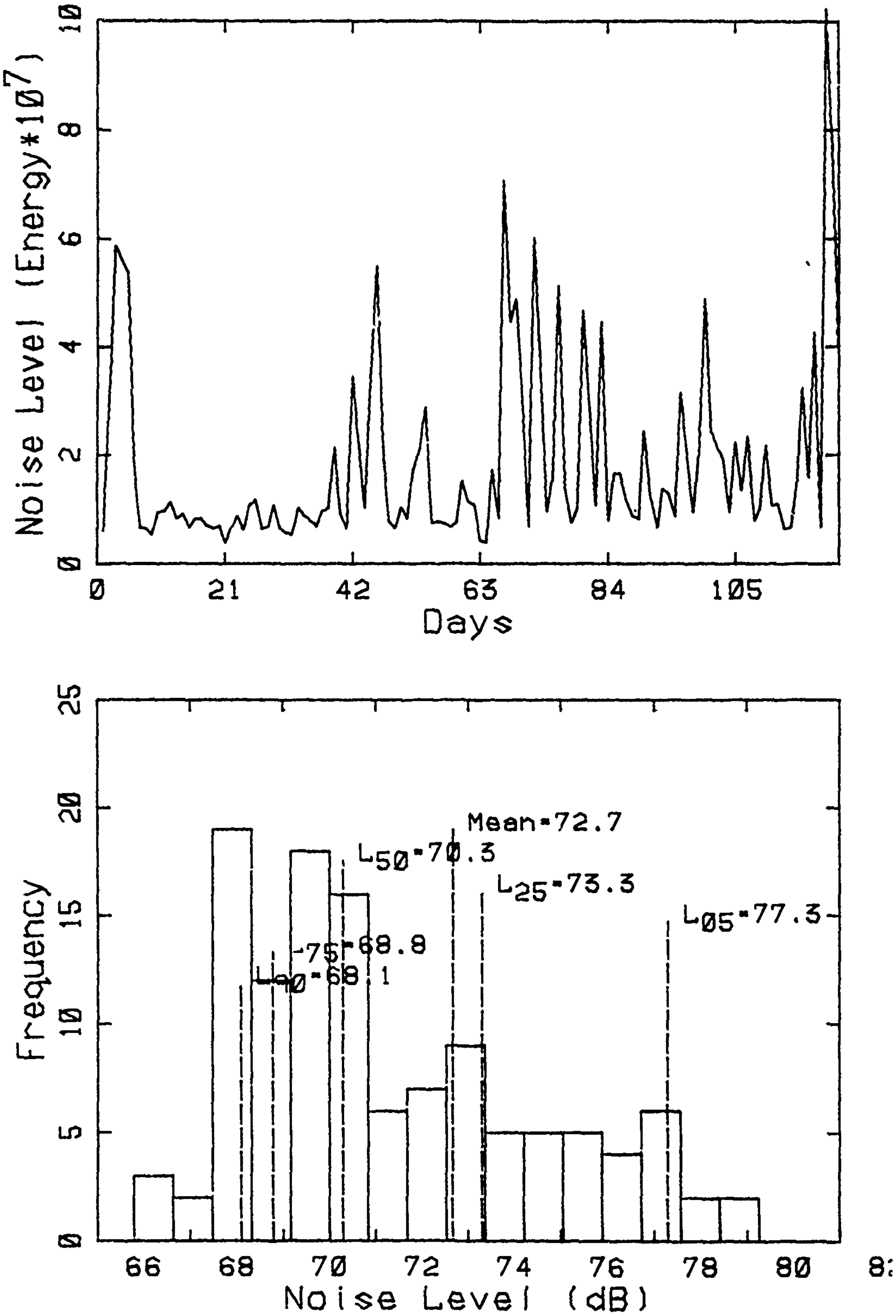
Boston Logan Site 3A



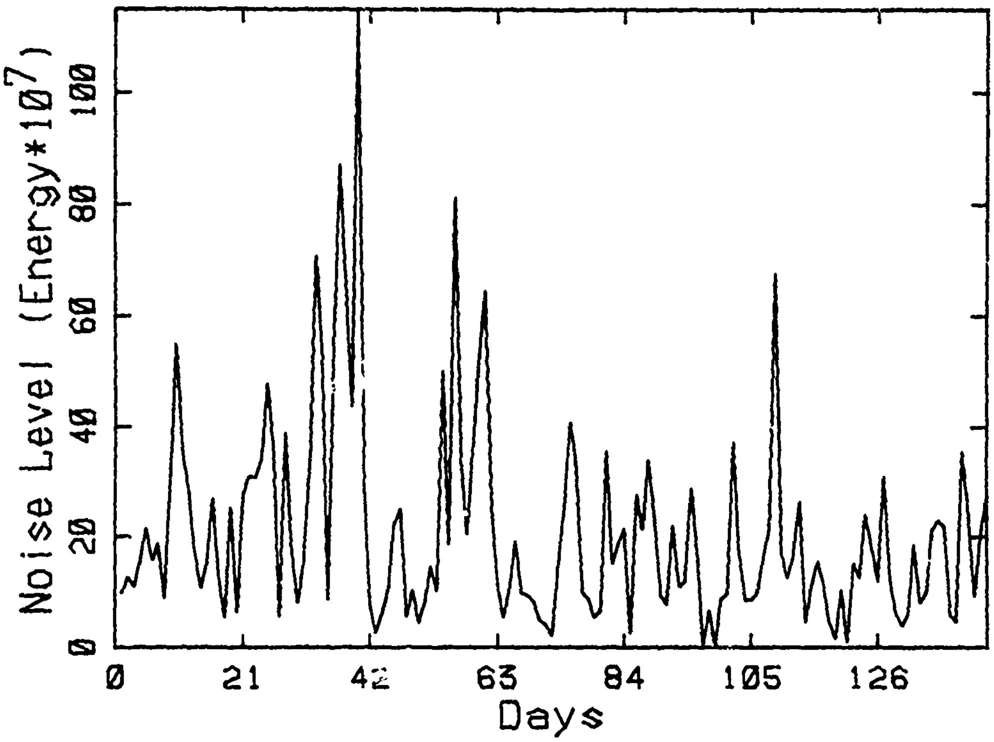
Boston Logan Site 3B

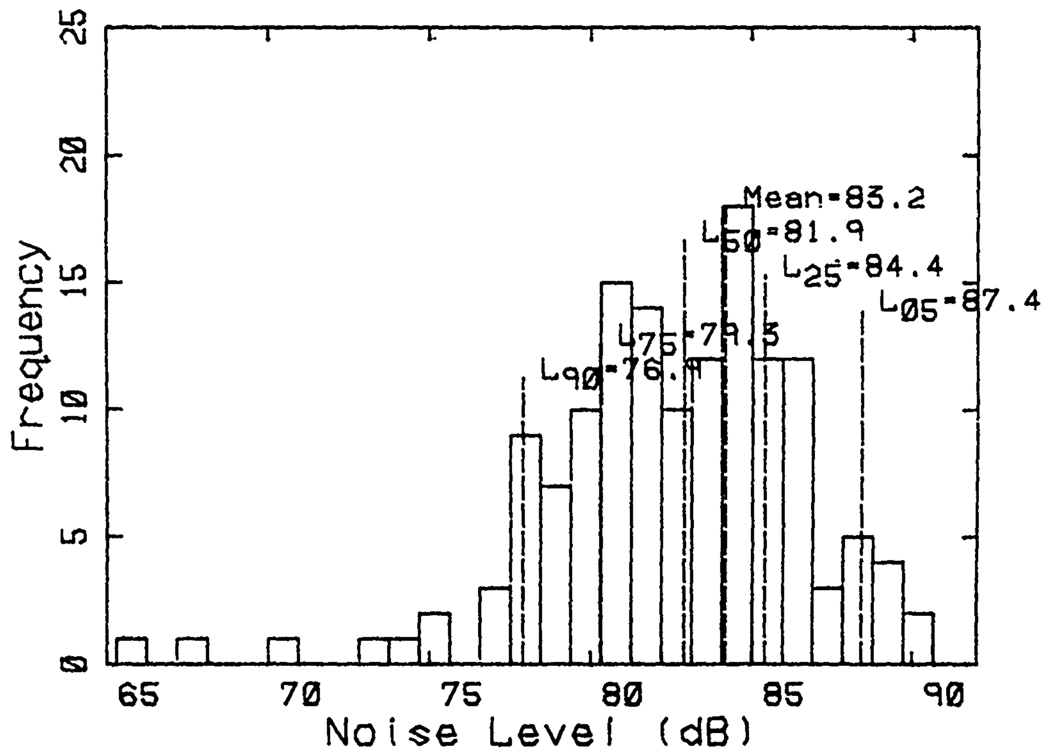


Boston Logan Site 4A

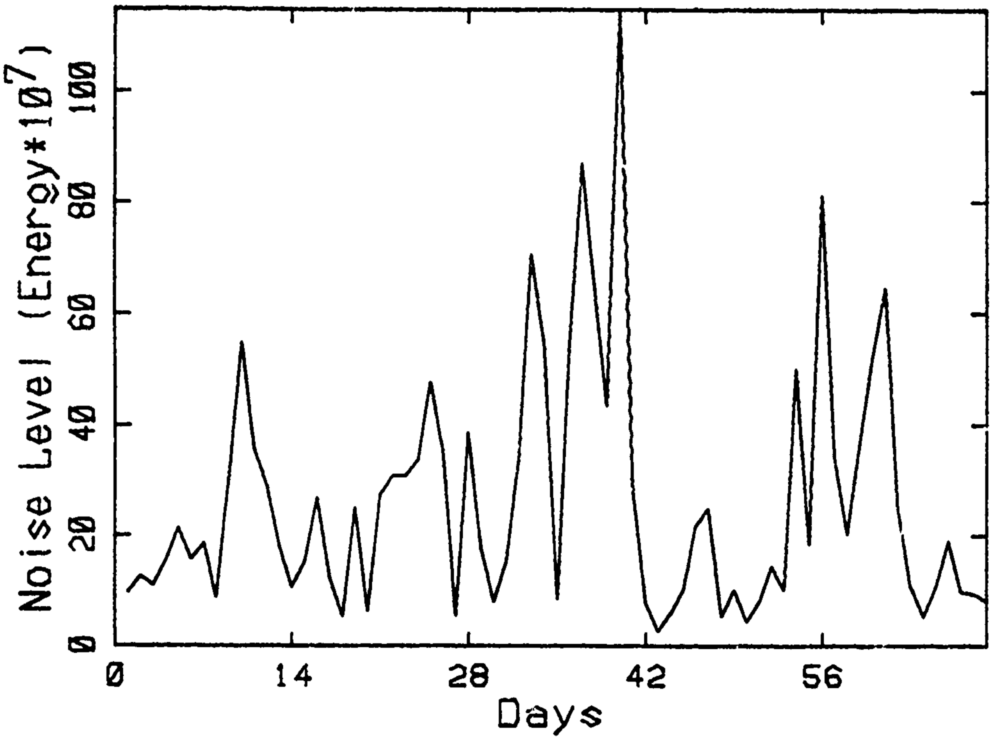


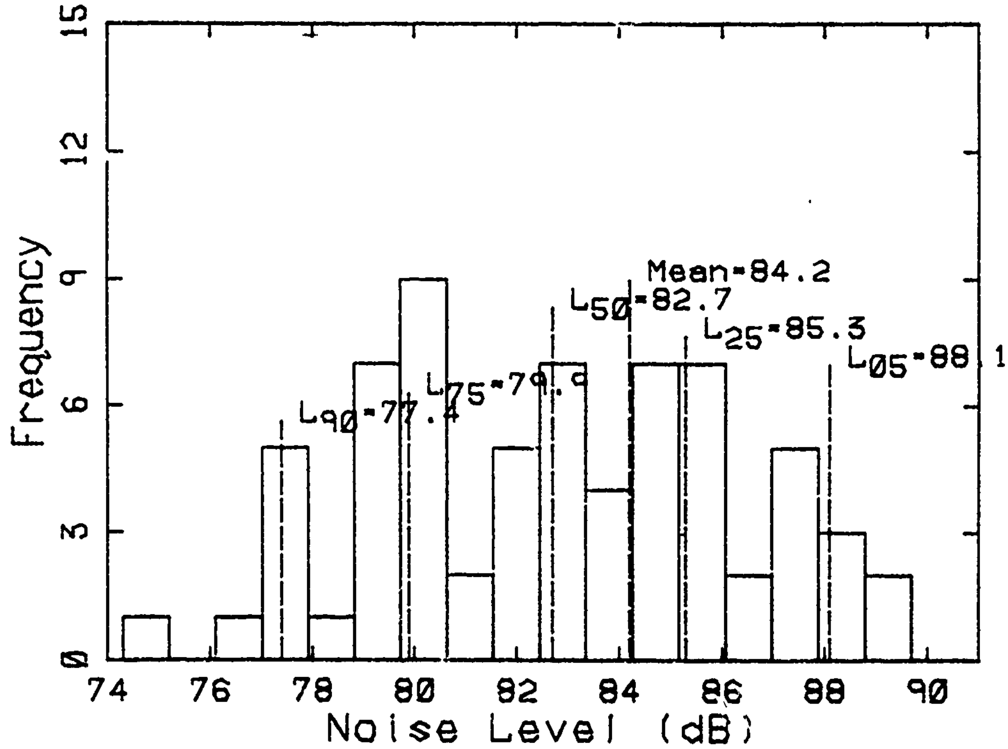
Boston Logan Site 4B



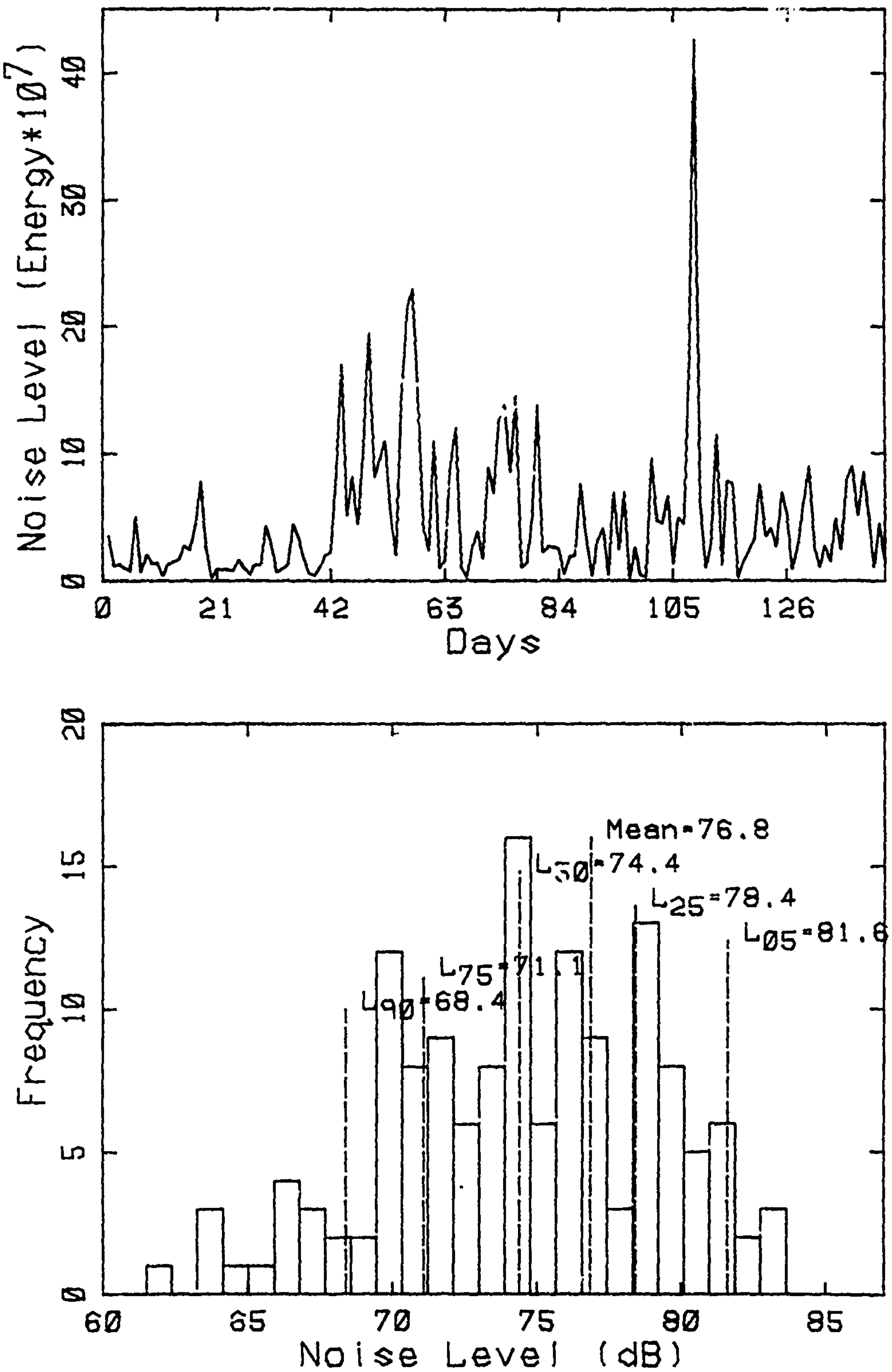


Boston Logan Site 5A

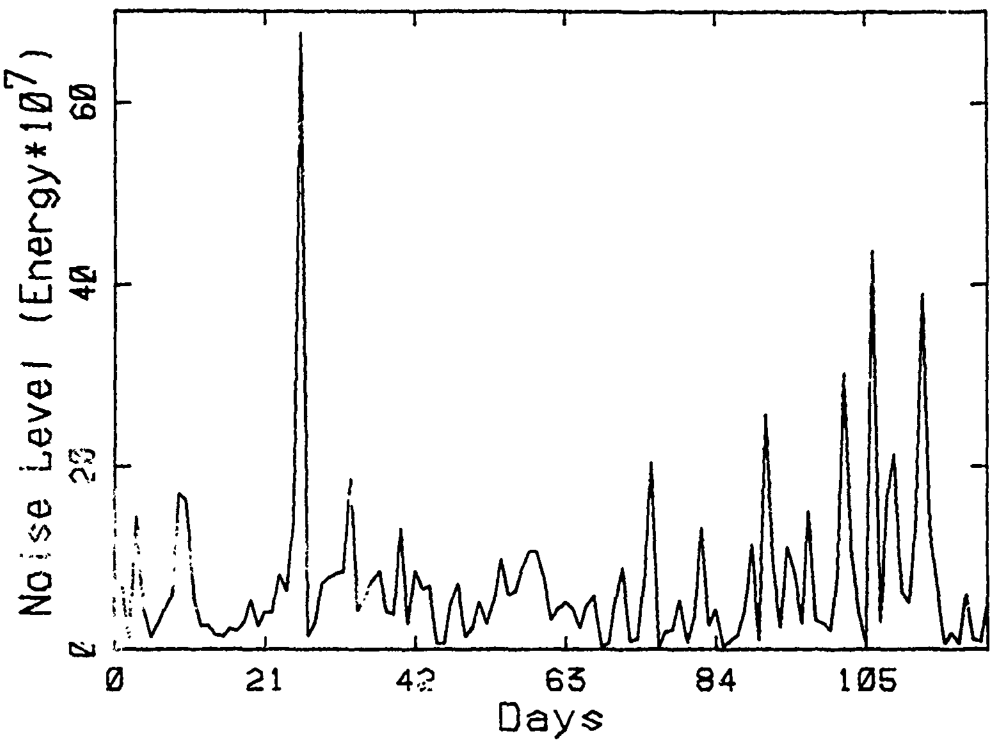


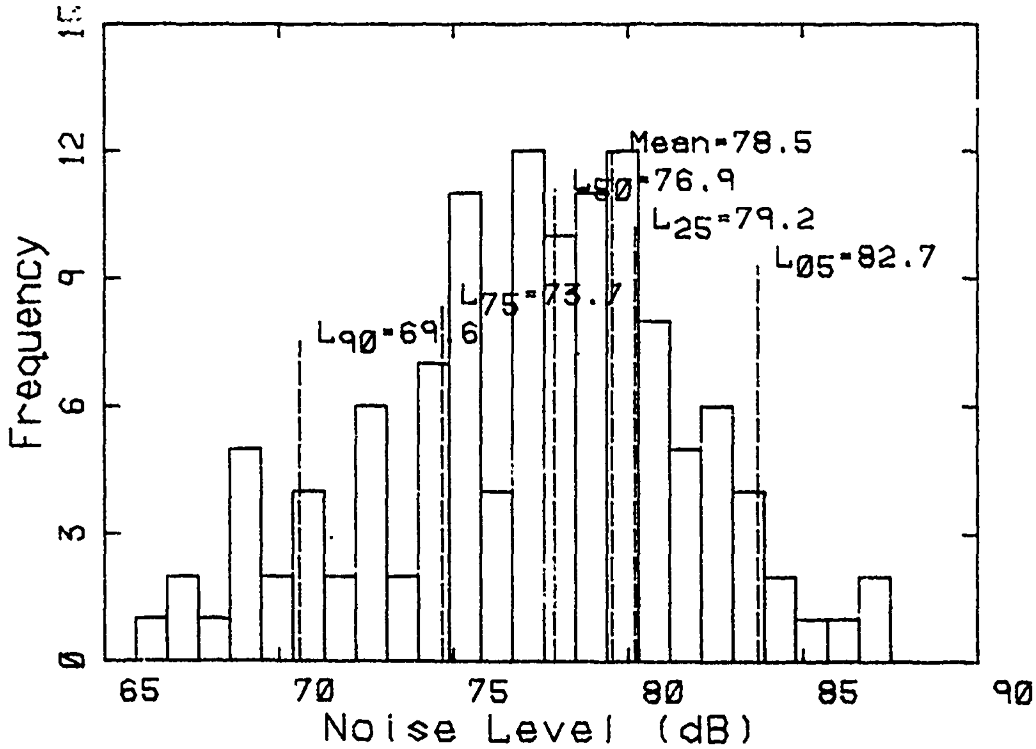


Boston Logan Site 5B

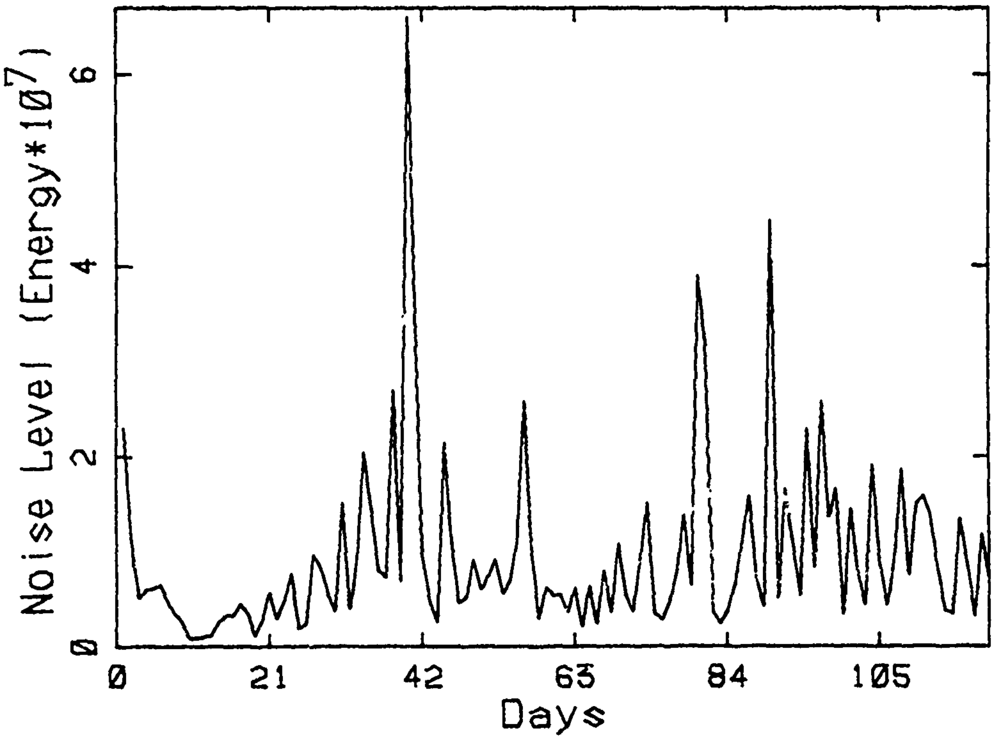


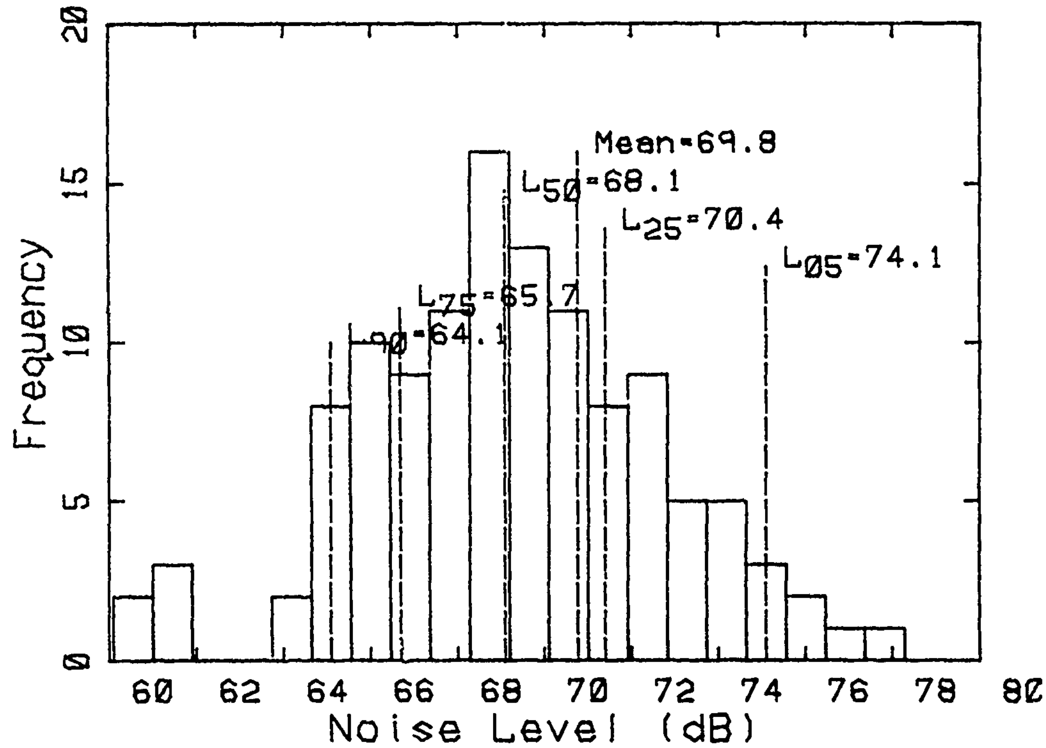
** BOSTON LOGAN AIRPORT - SITE 6A



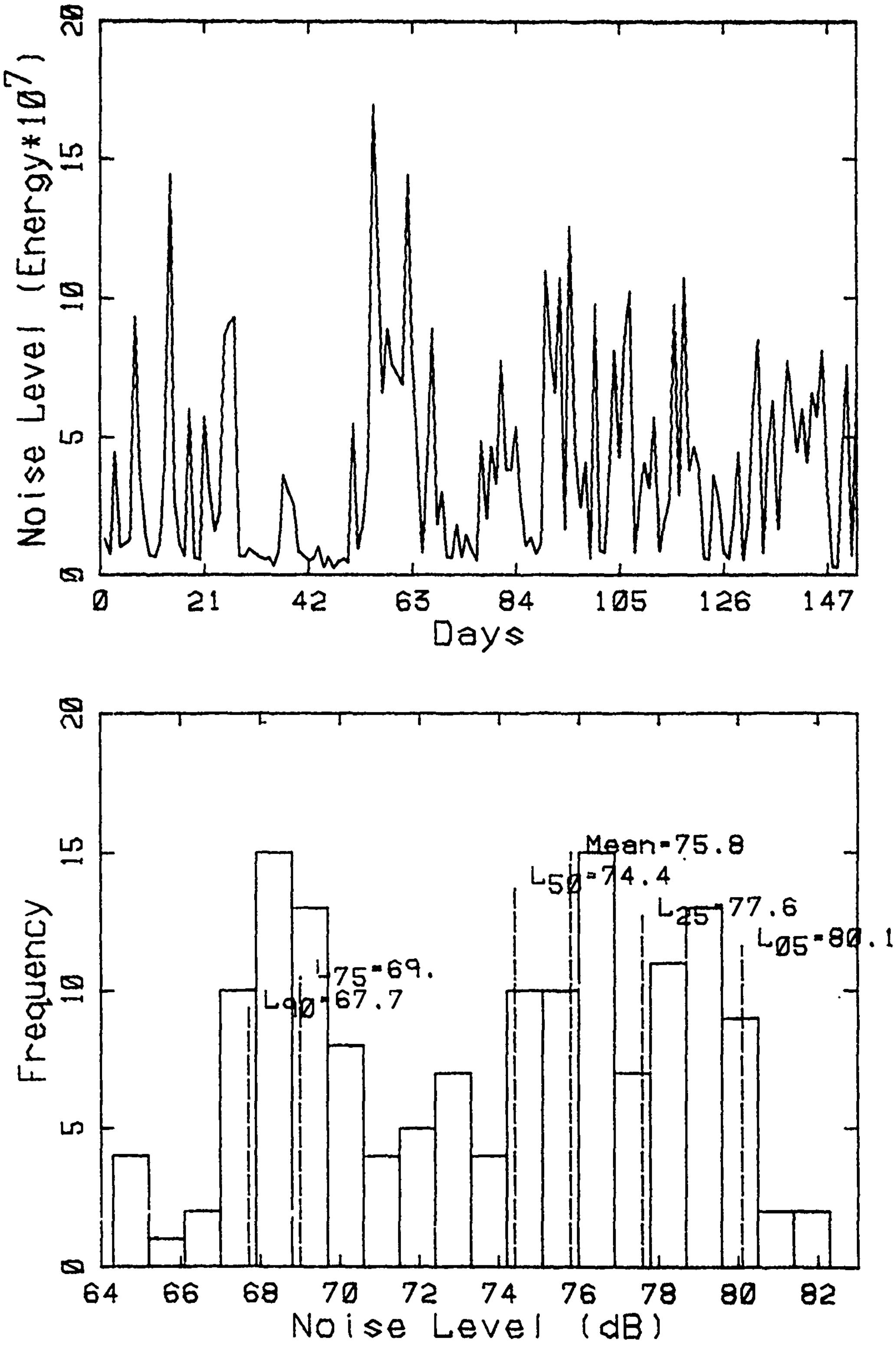


Boston Logan Site 6B

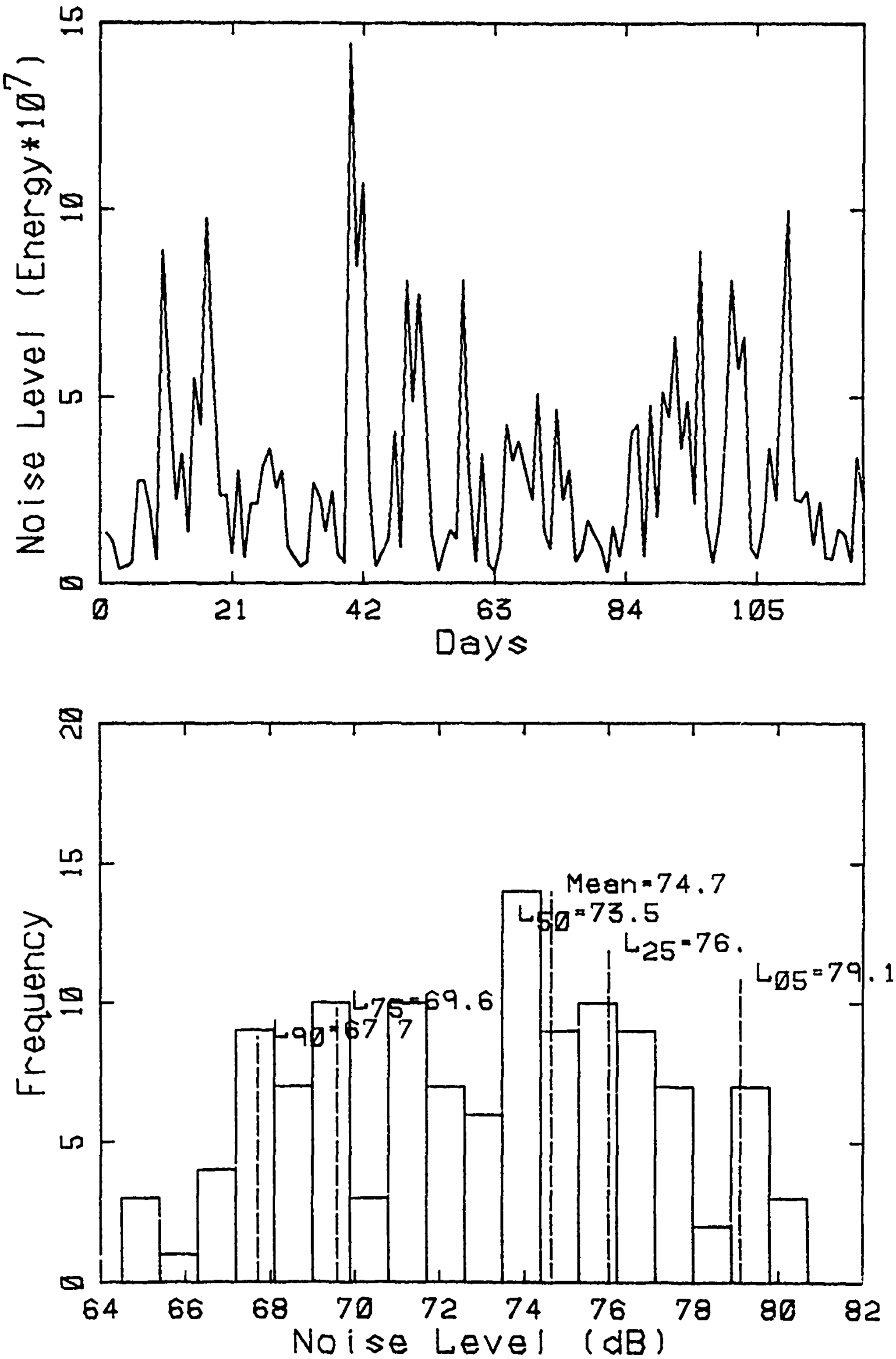




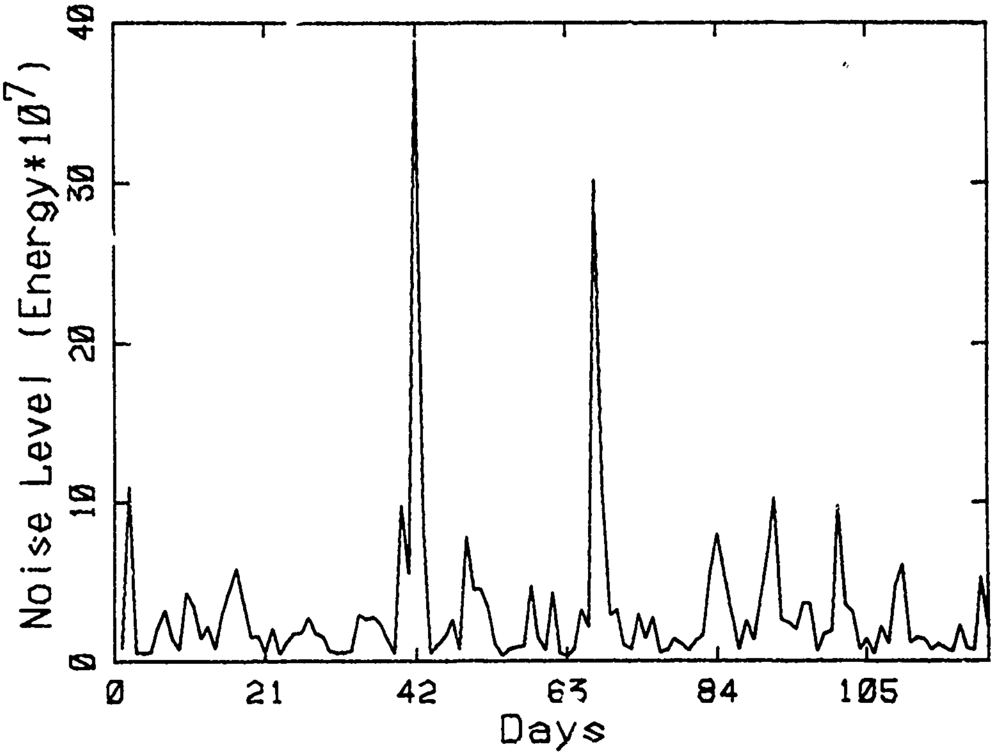
Boston Logan Site 7

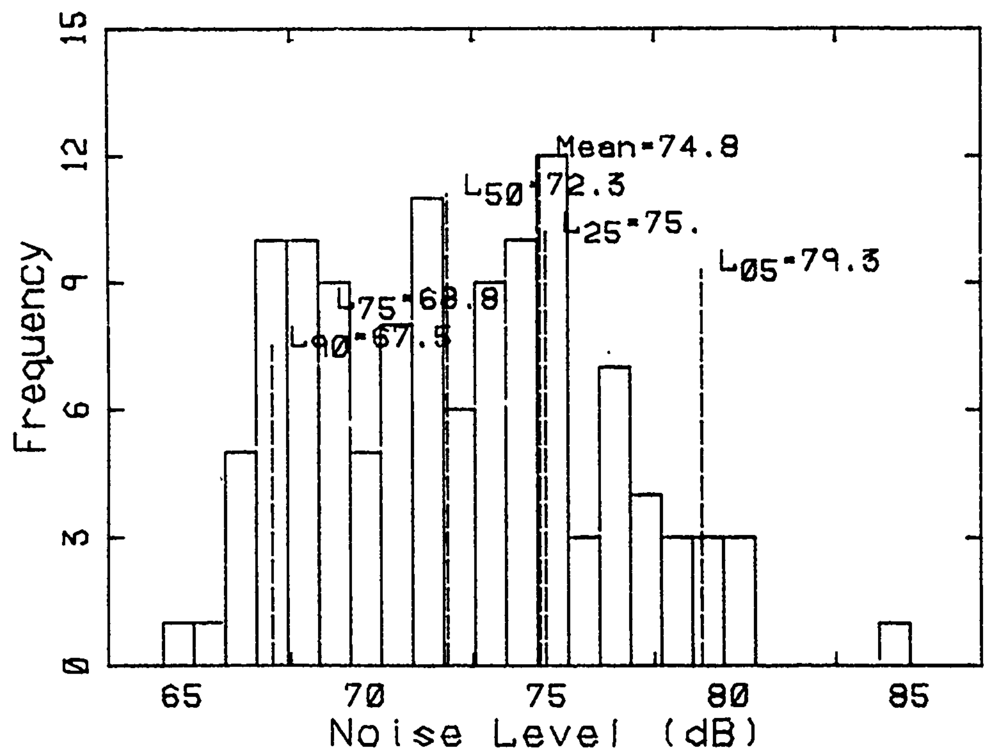


Boston Logan Site 8A

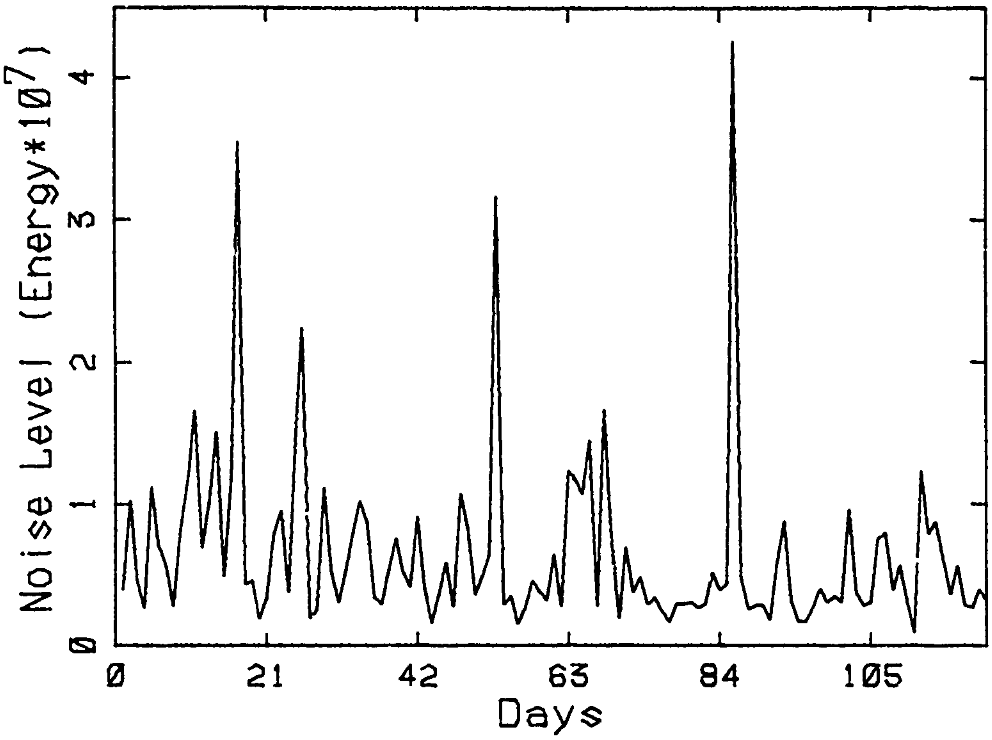


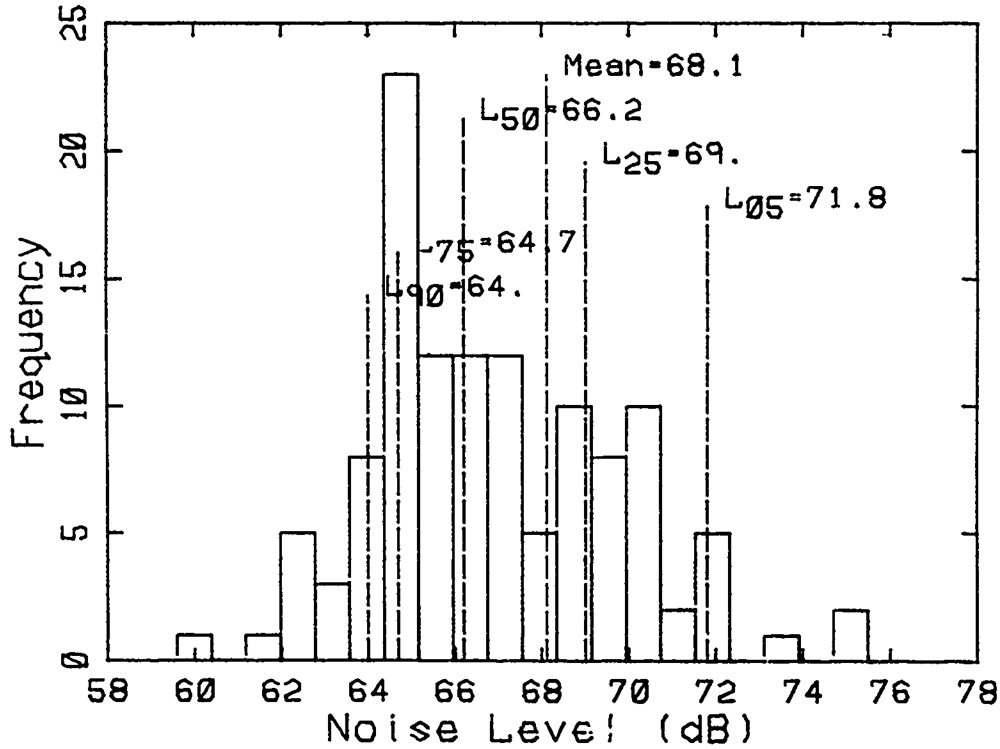
Boston Logan Site 8B



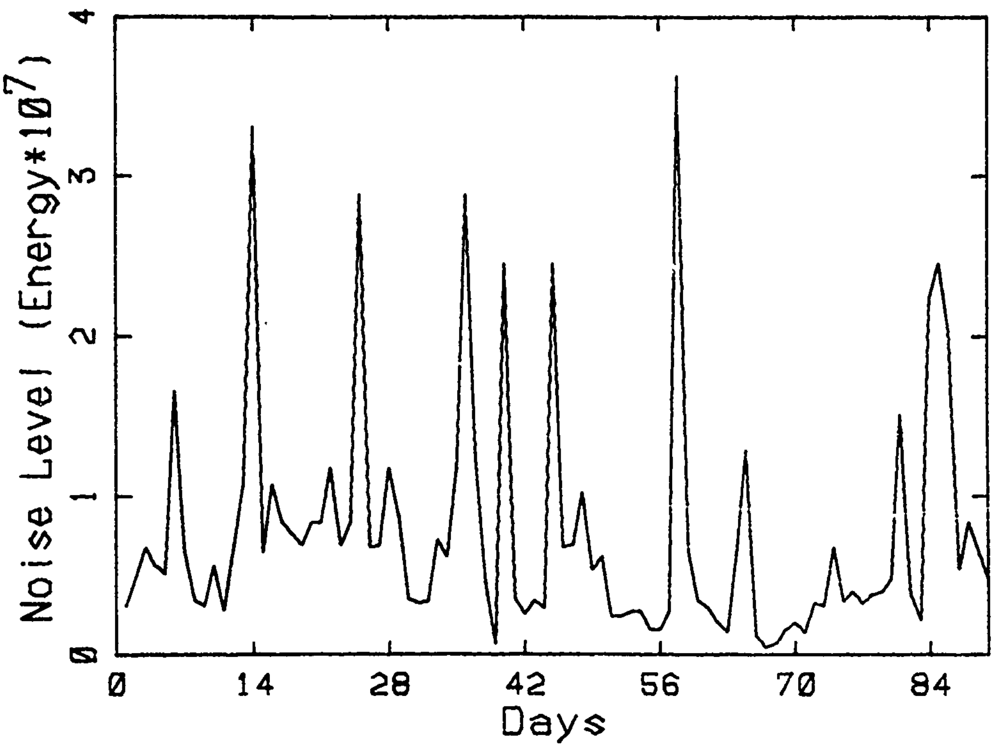


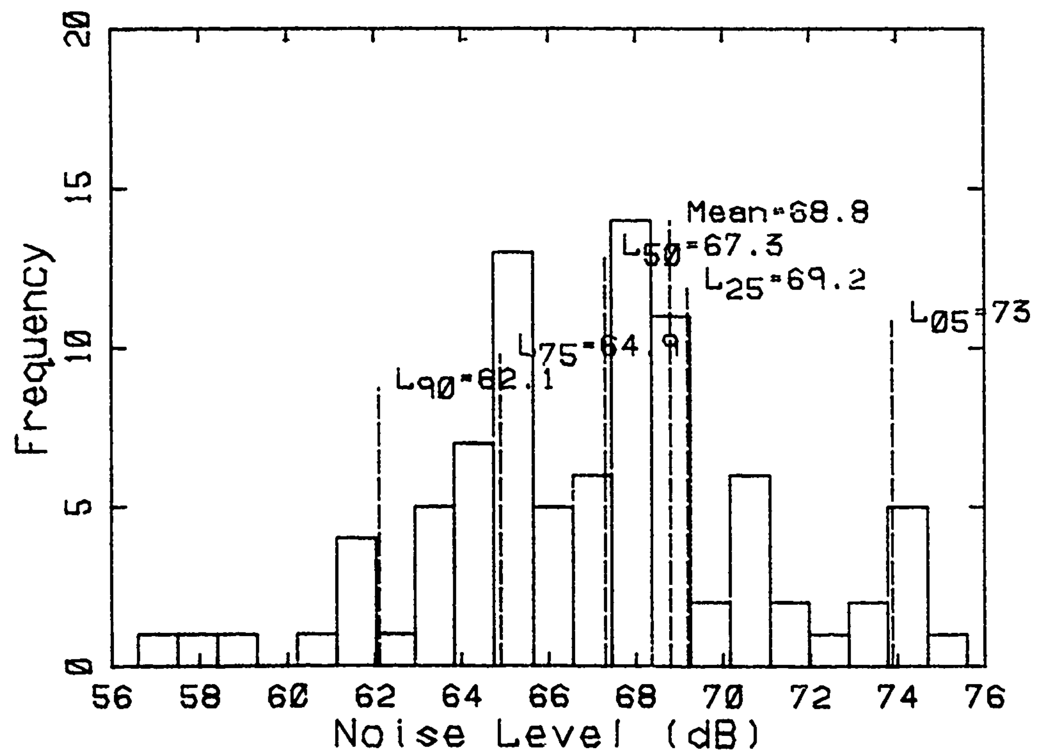
Boston Logan Site 9



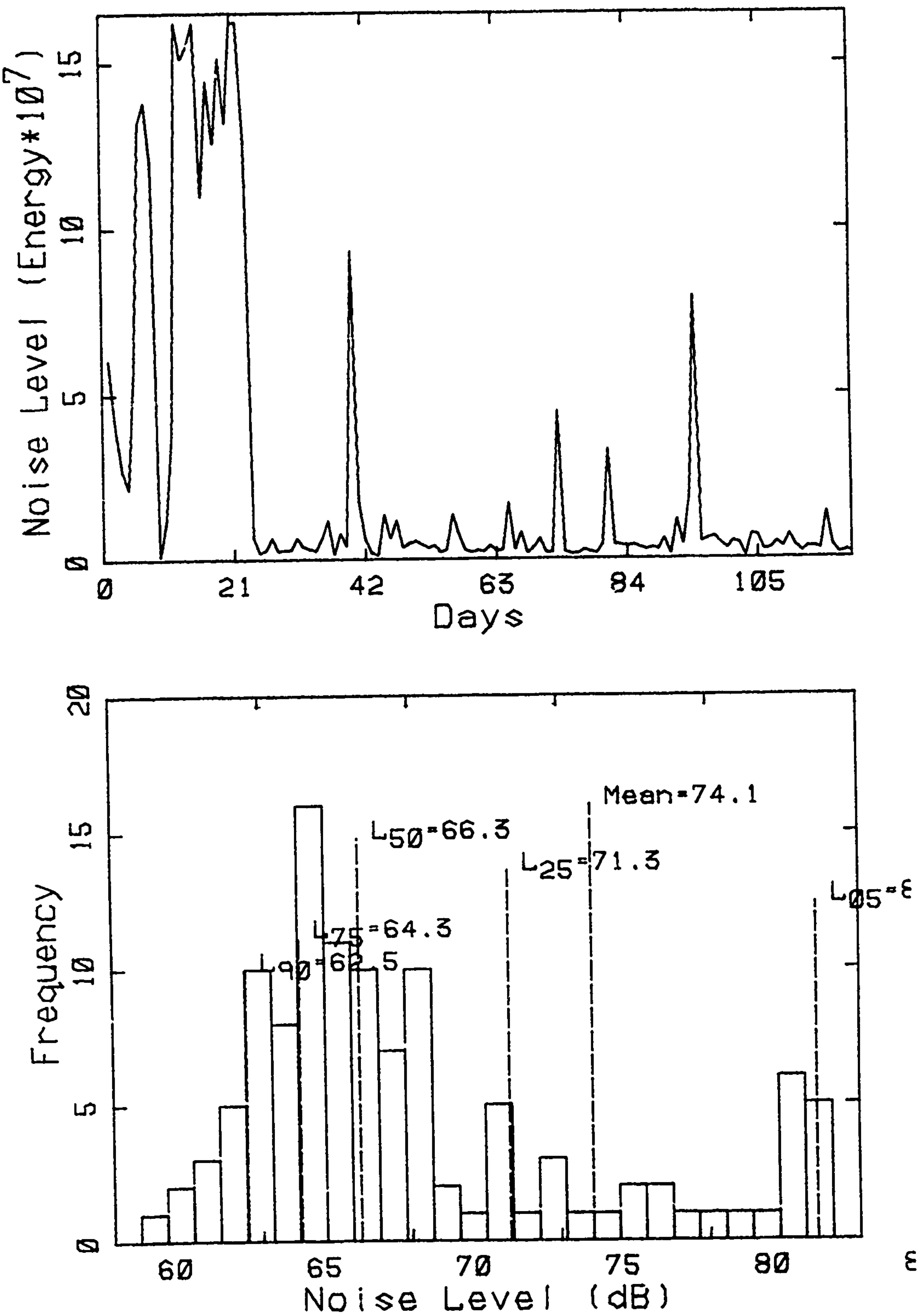


Boston Logan Site 10

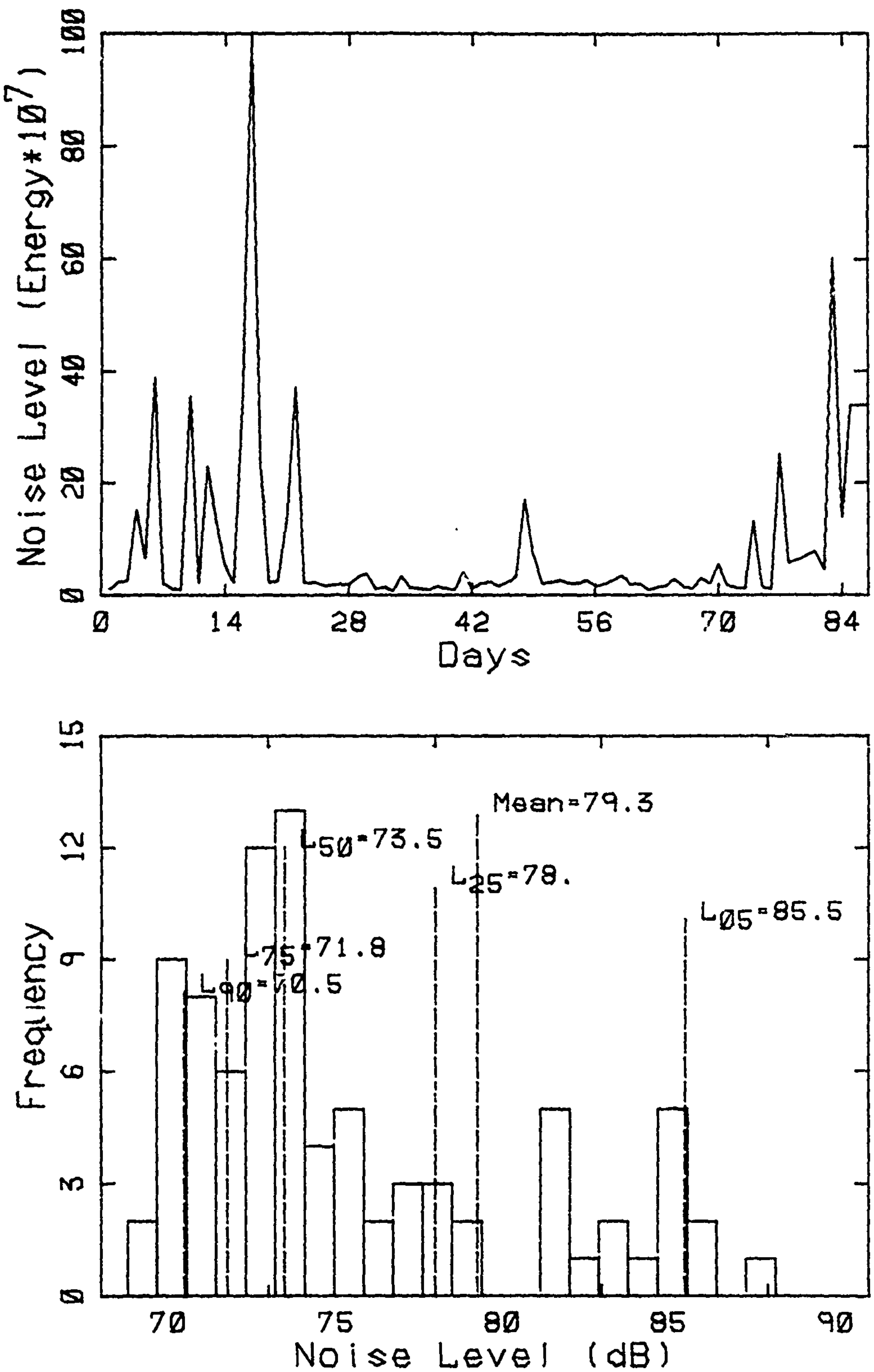




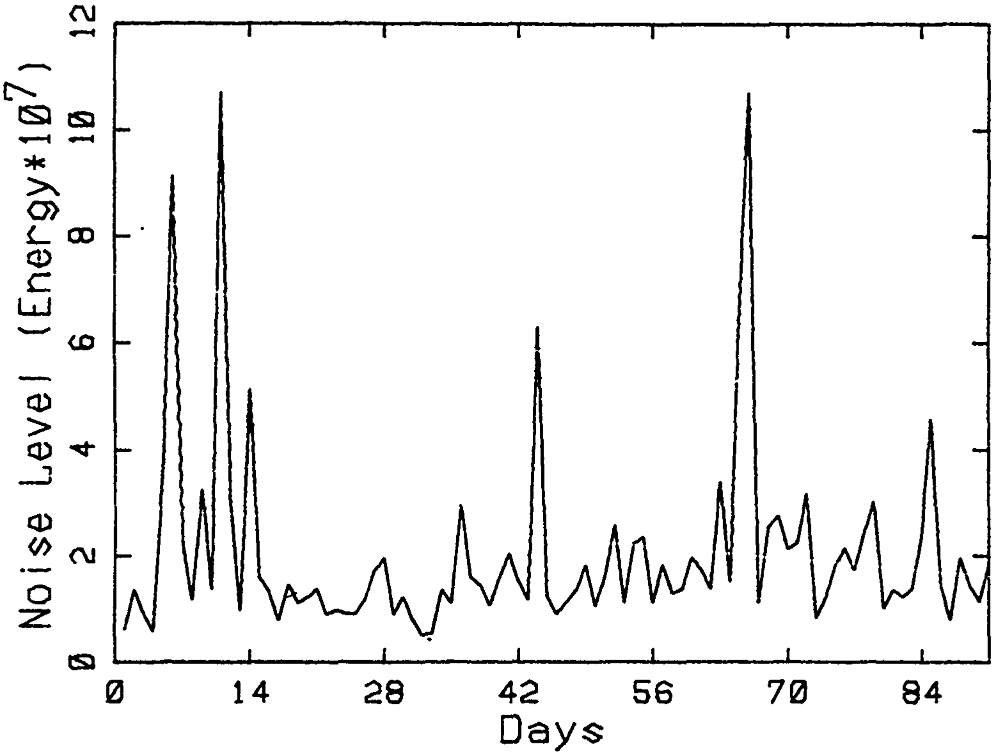
Boston Logan Site 11A

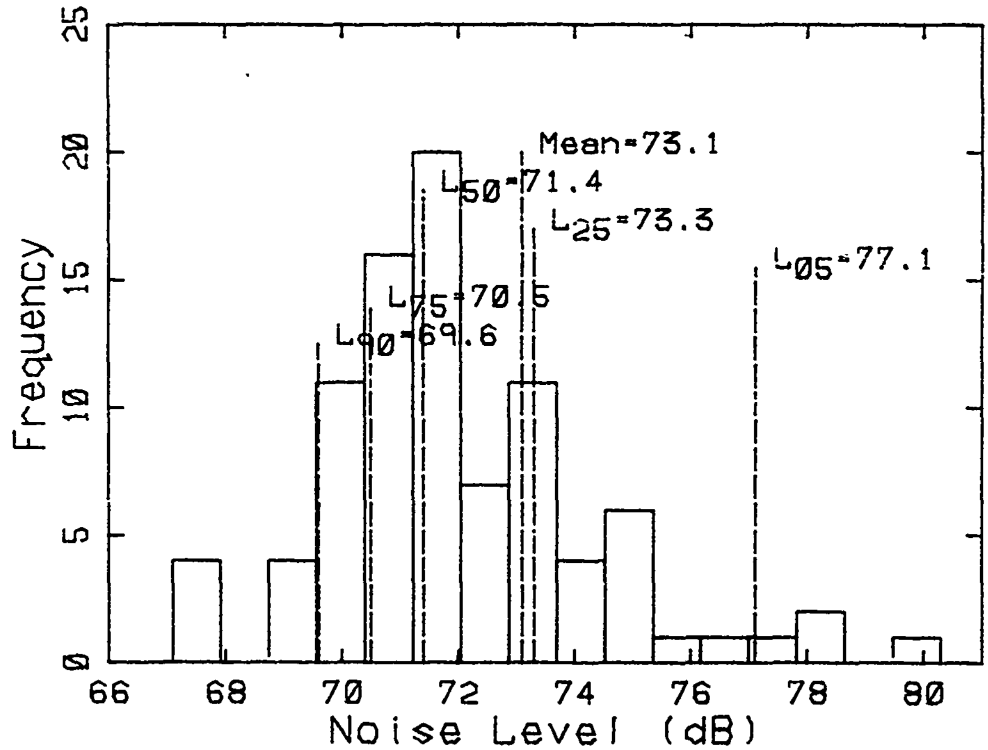


Boston Logan Site 11B



Boston Logan Site 12A





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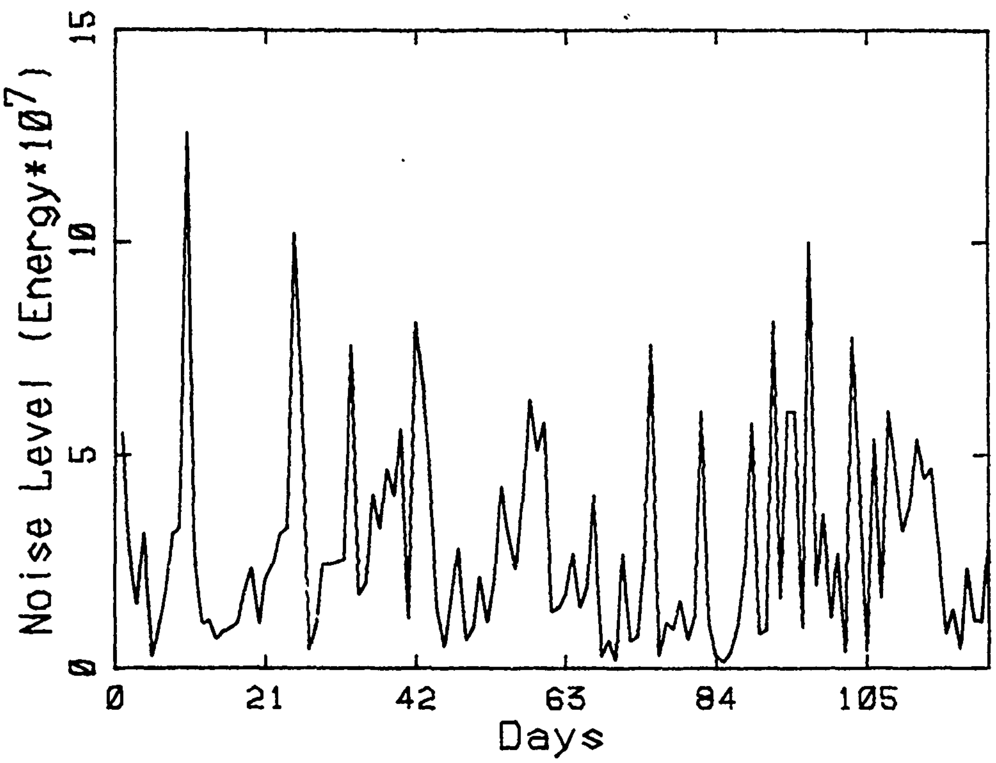
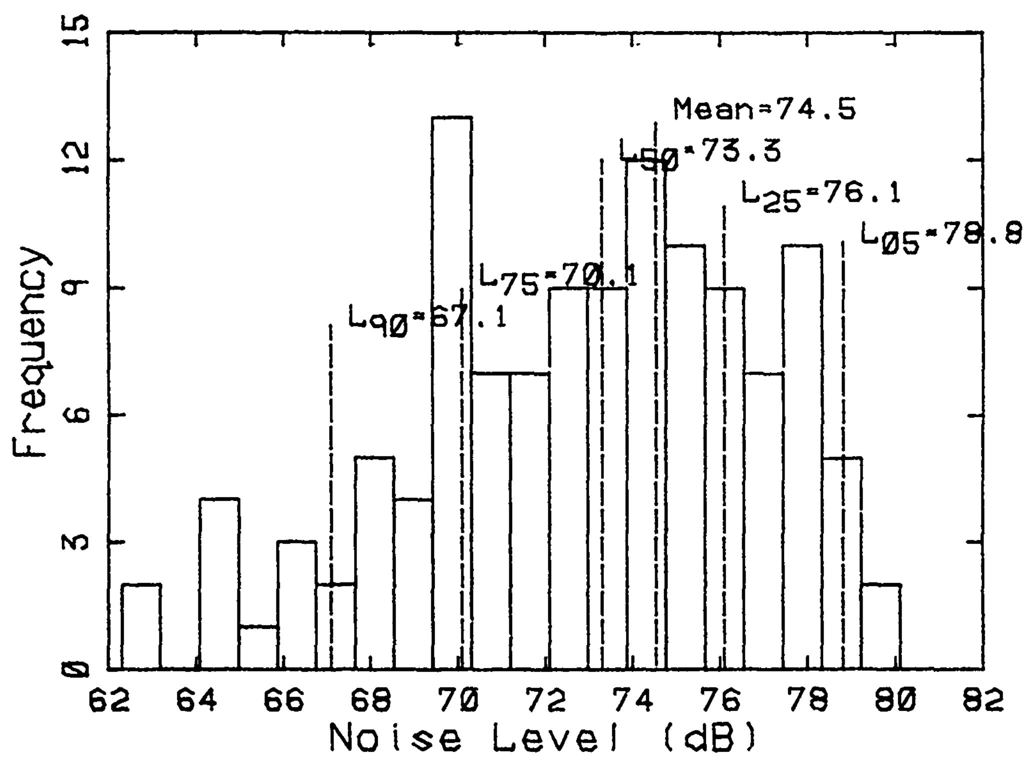
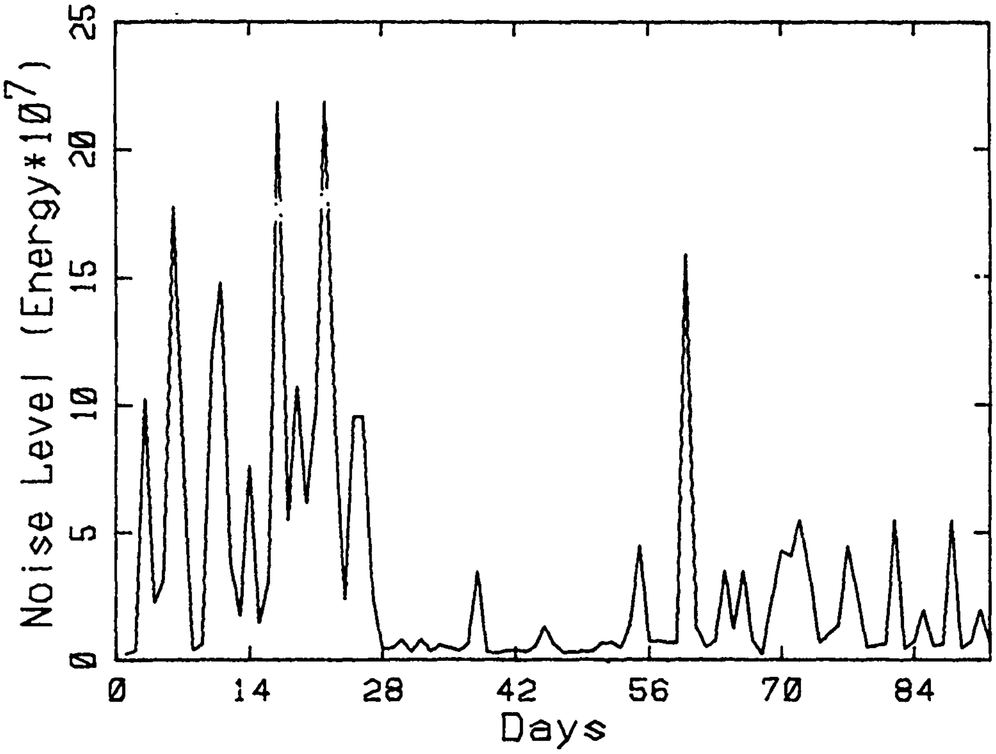
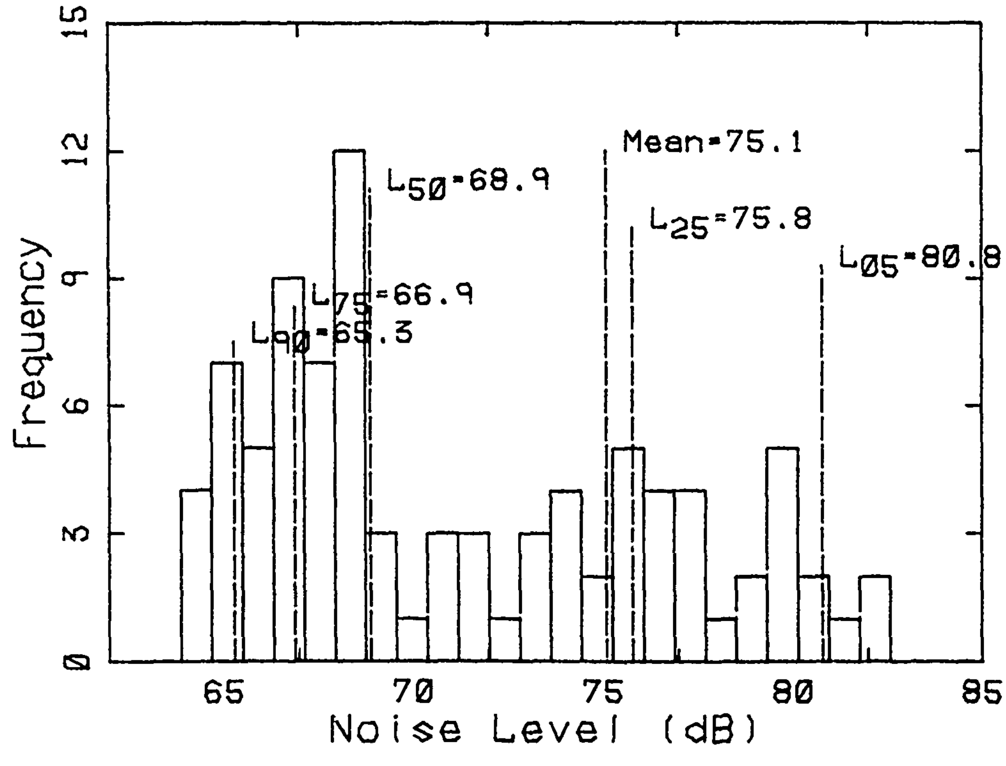


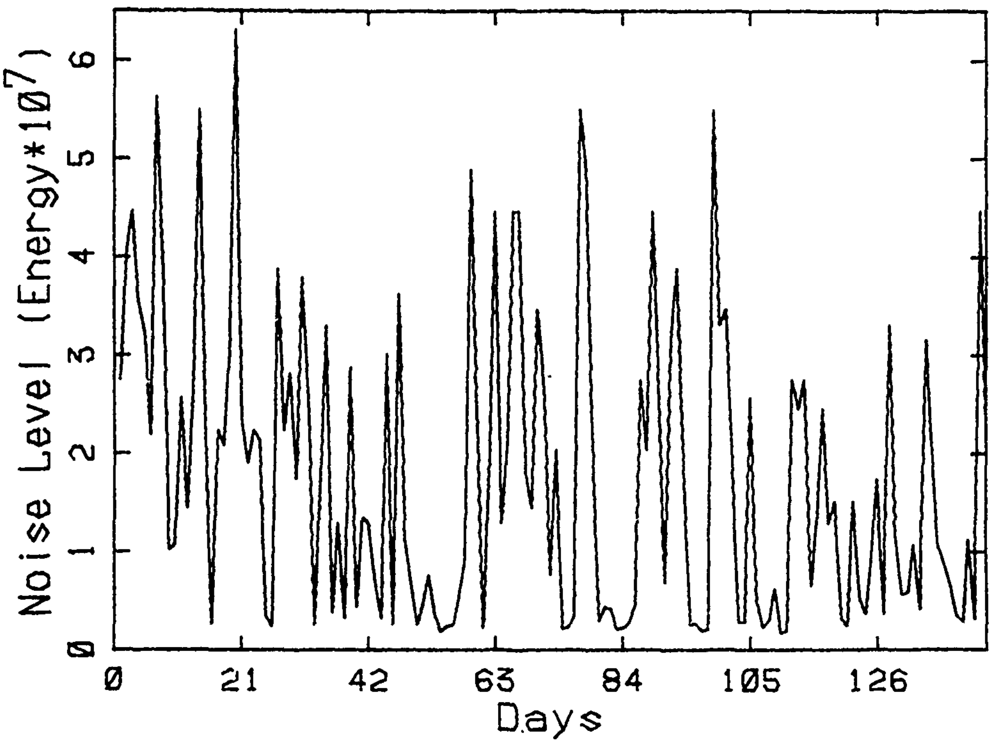


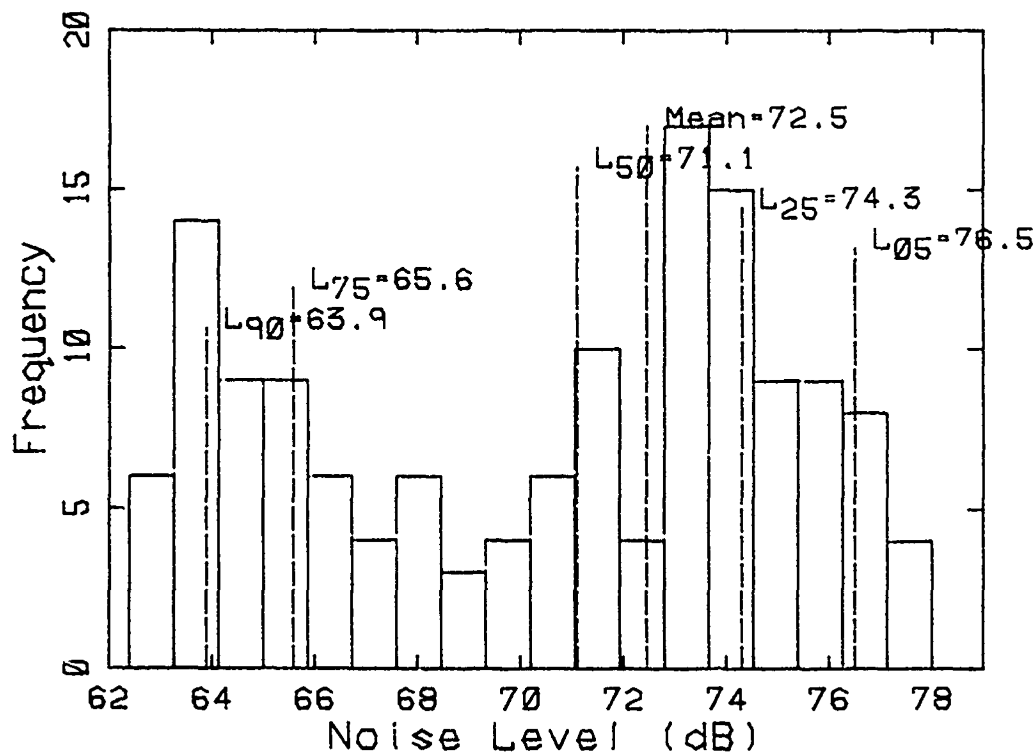
Boston Logan Site 13A





Boston Logan Site 14

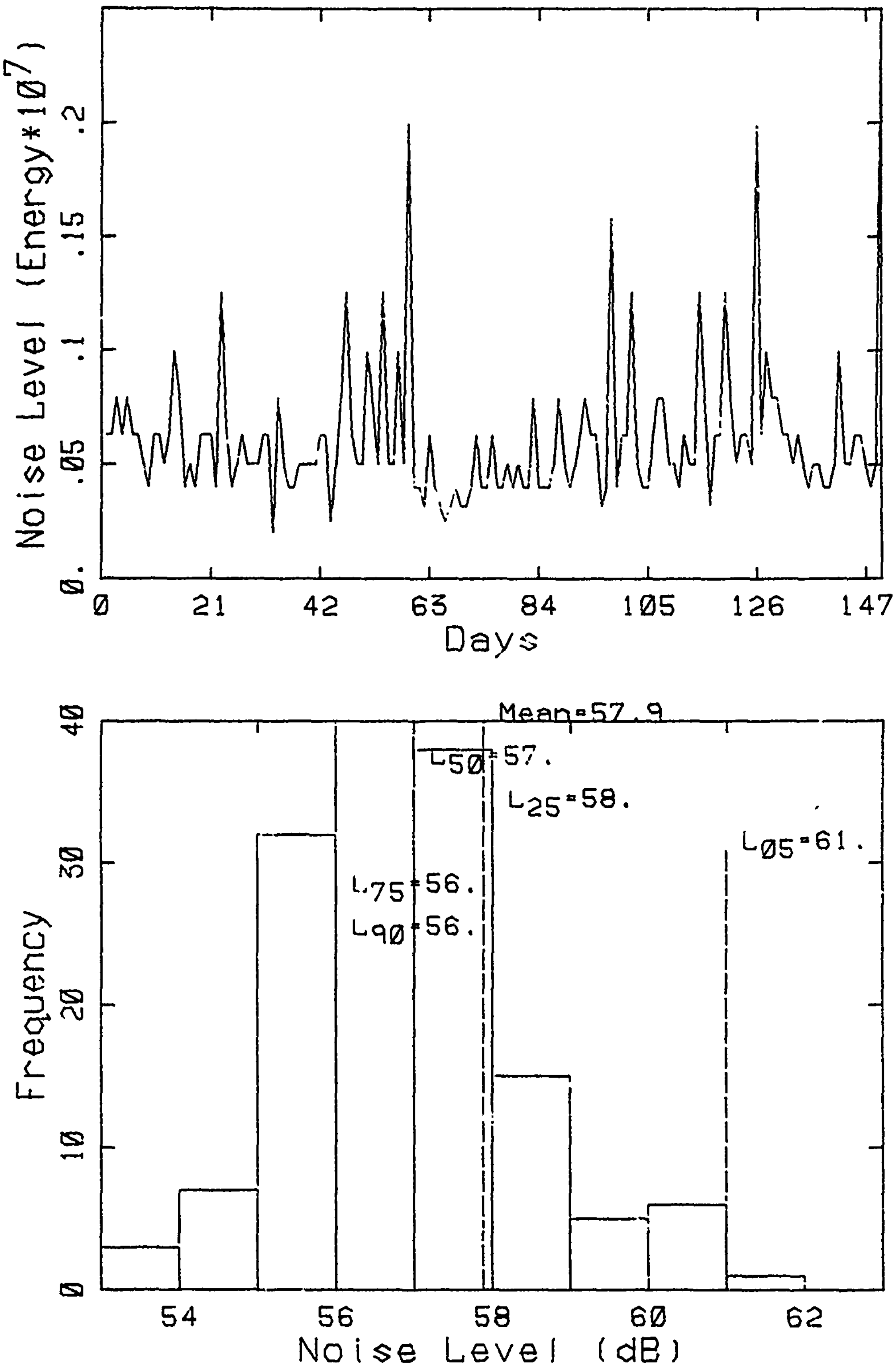




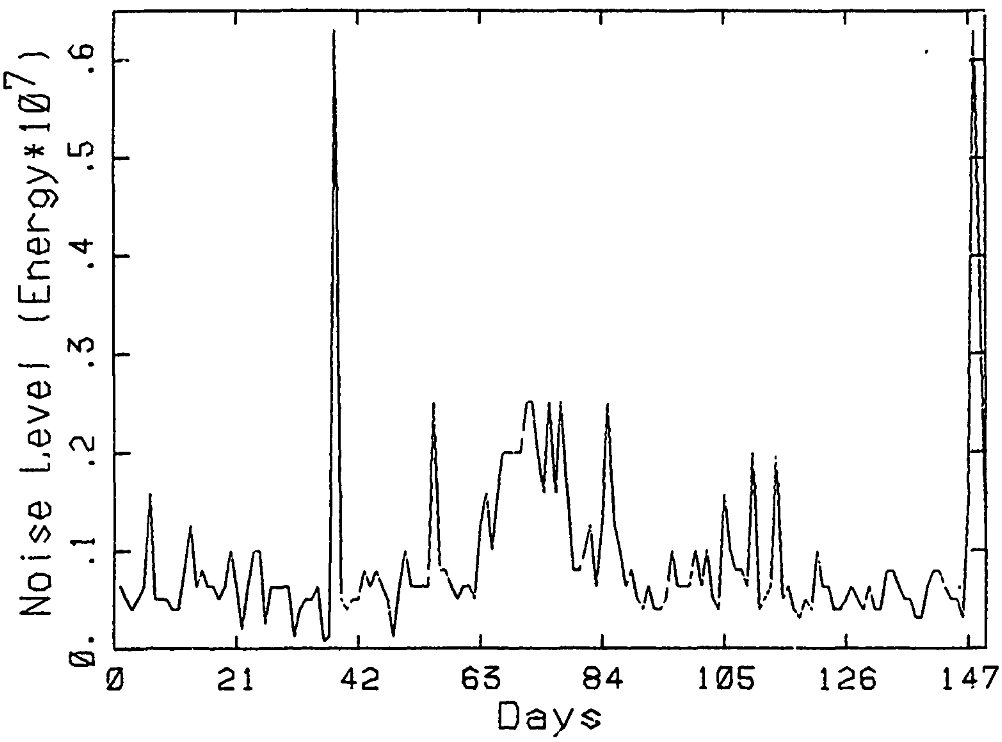
Boston Logan Site 15

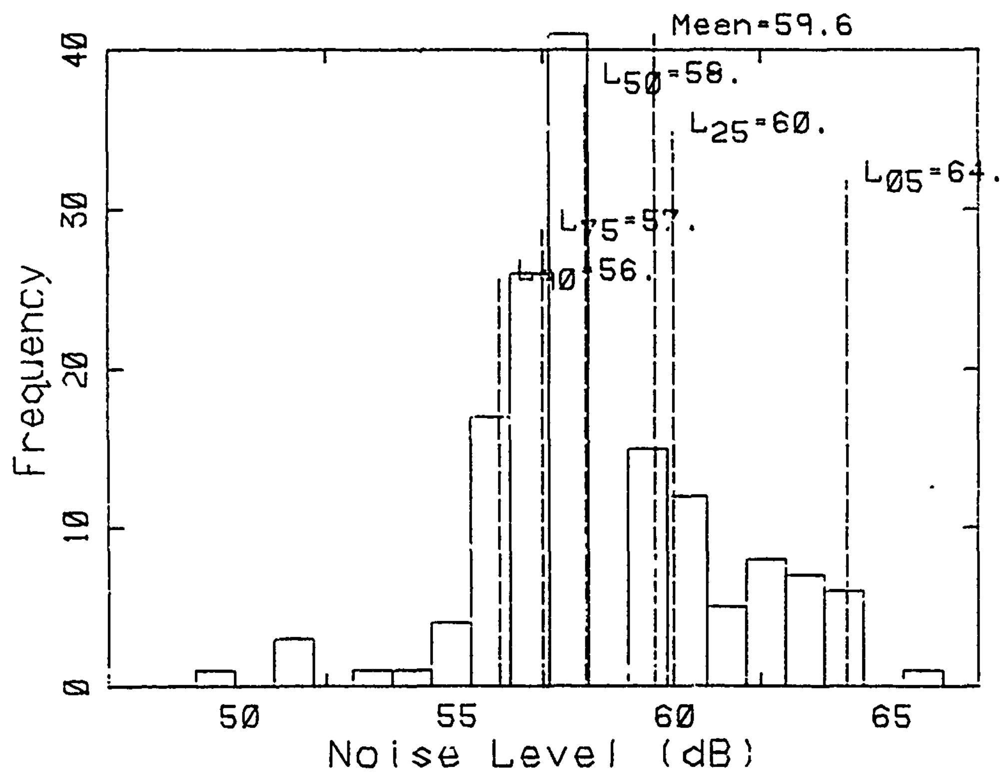
APPENDIX C:

WASHINGTON NATIONAL AND DULLES AIRPORTS HISTOGRAMS
AND TIME SERIES PLOTS



Wash. Duls. Site 1A





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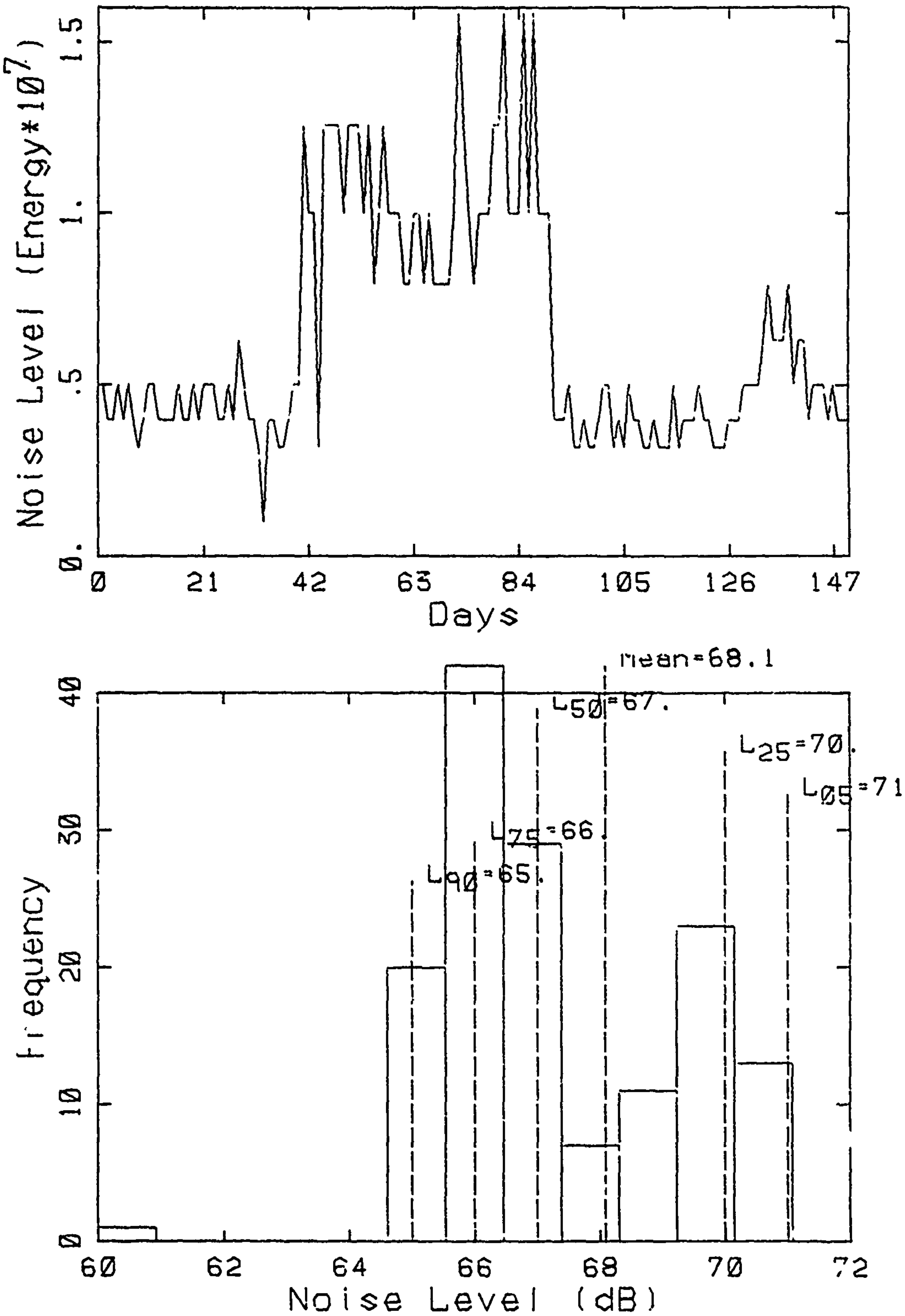

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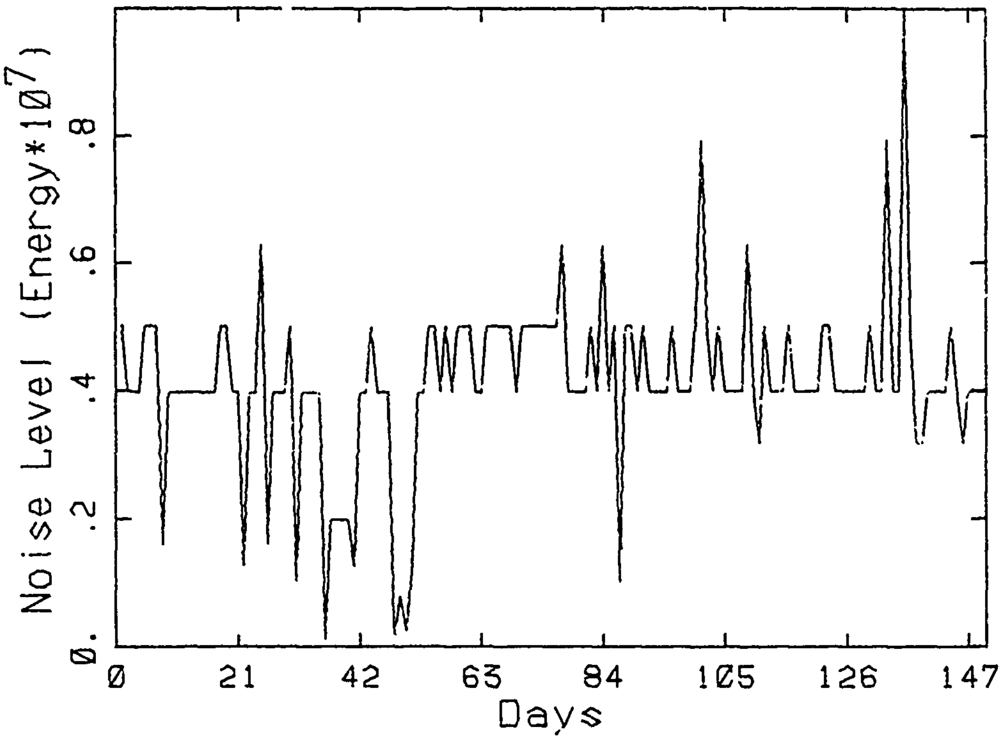

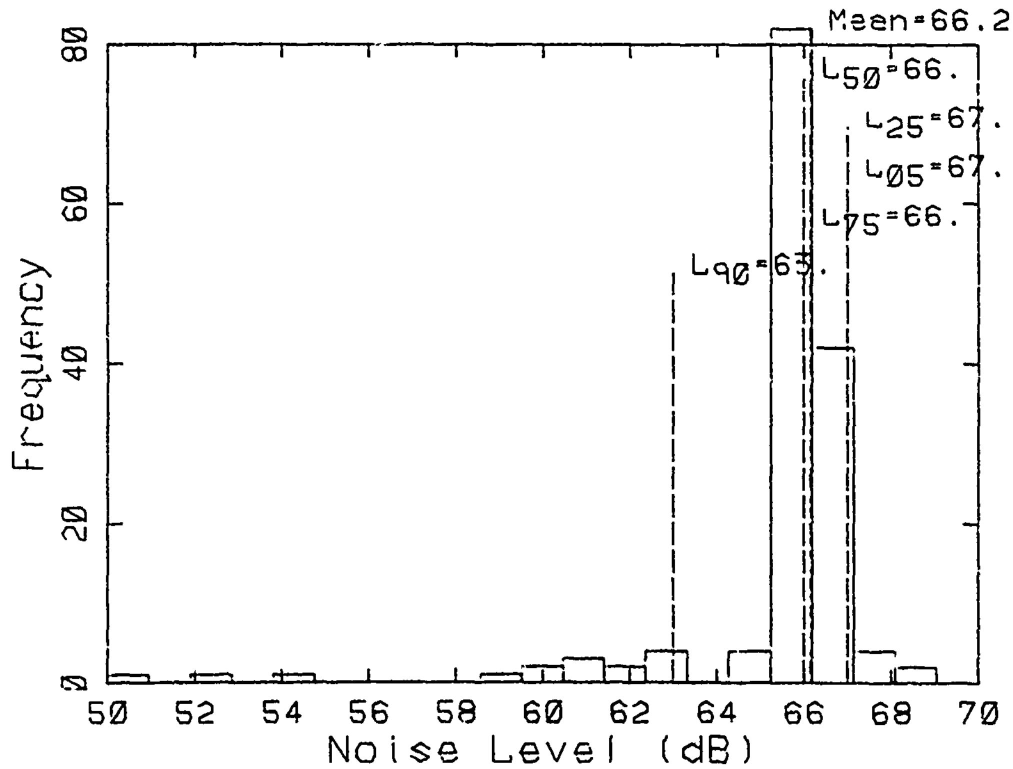

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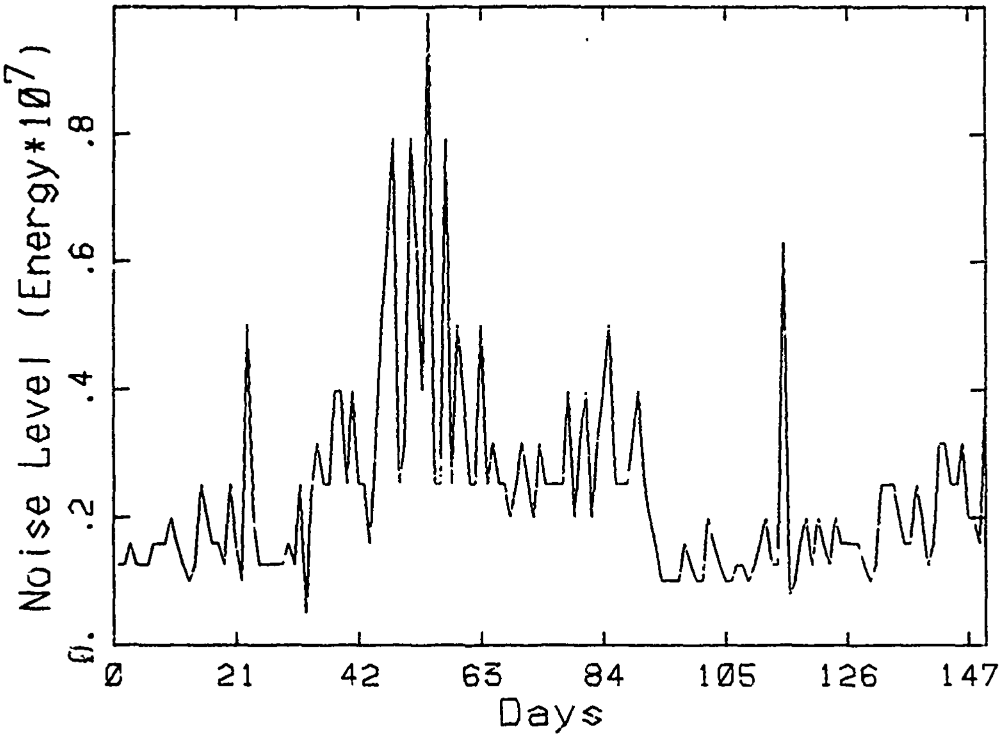

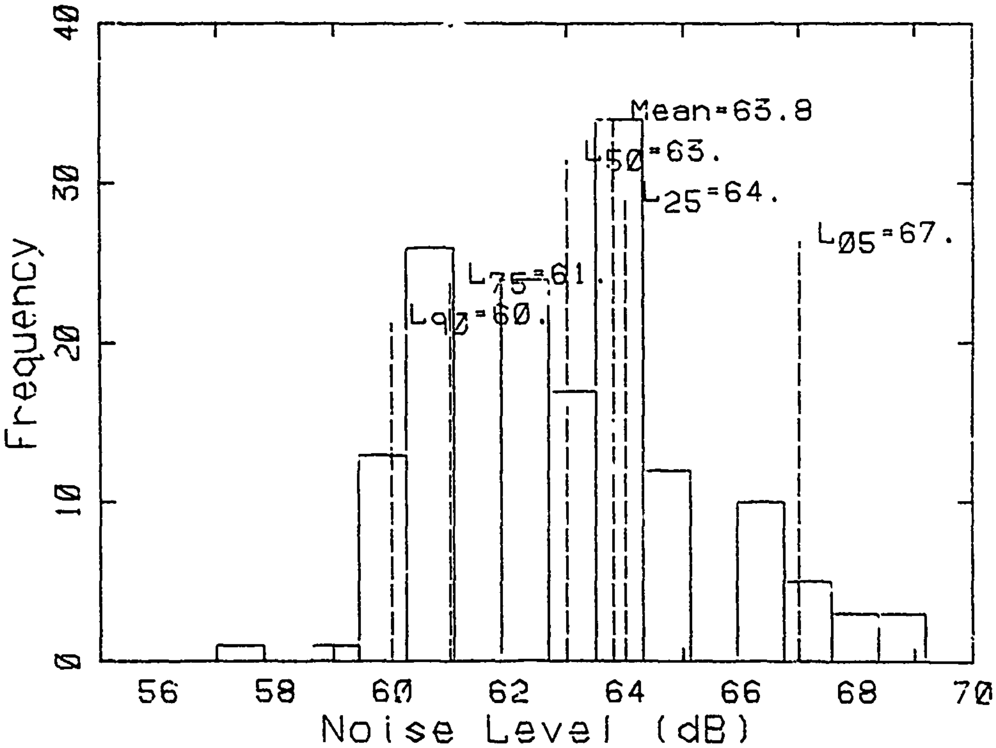

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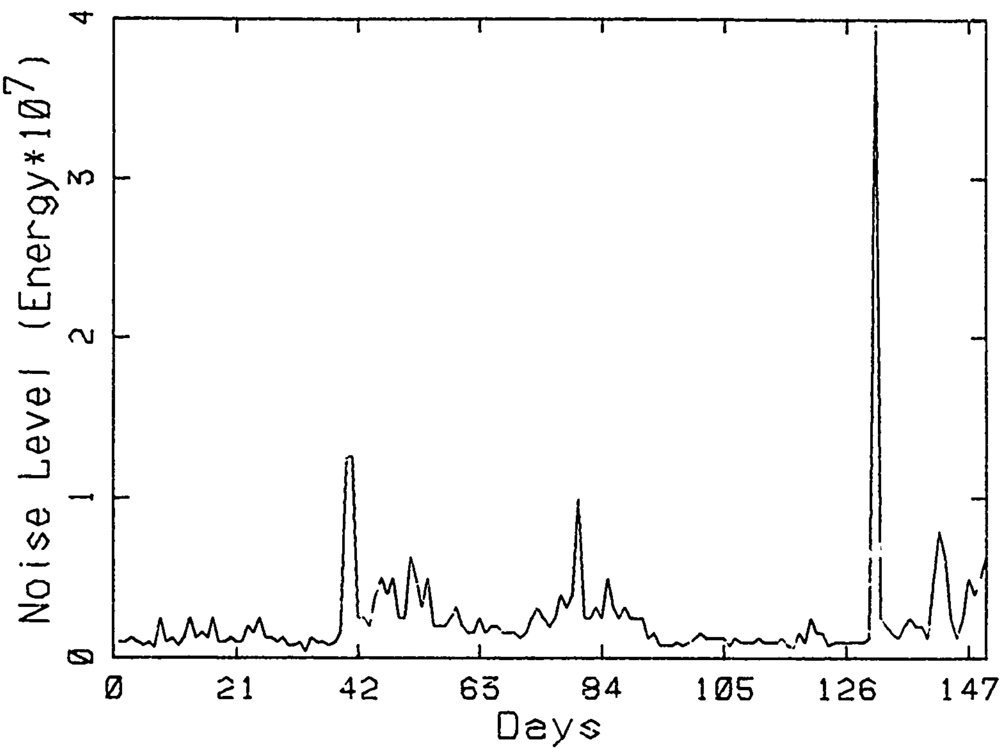

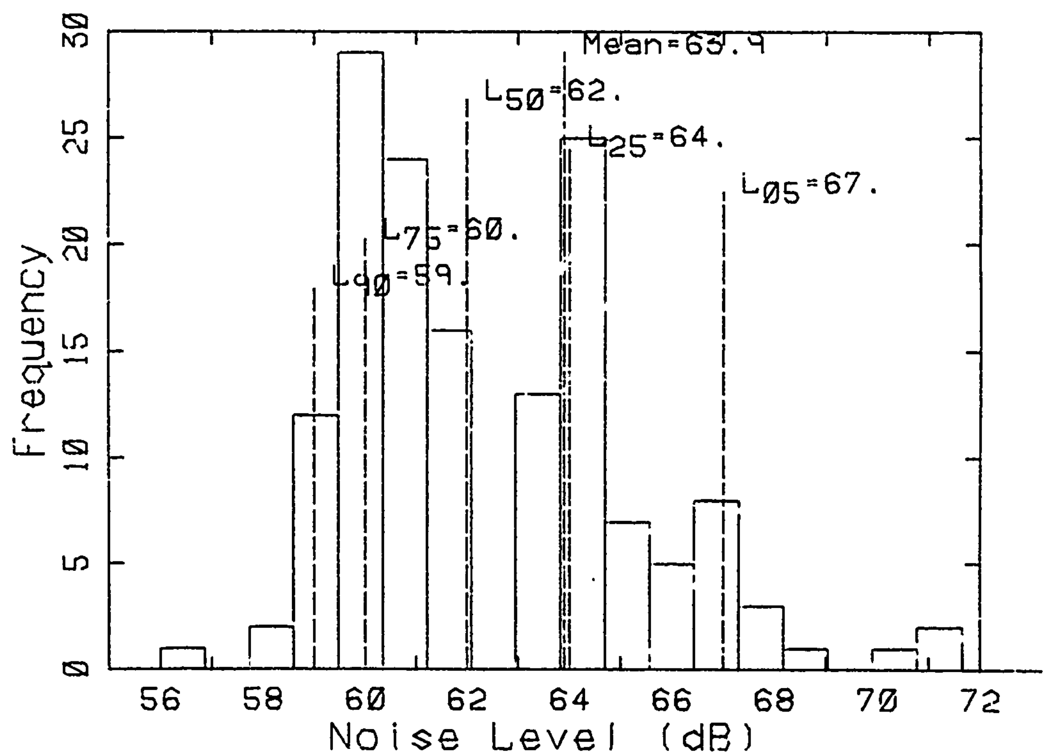

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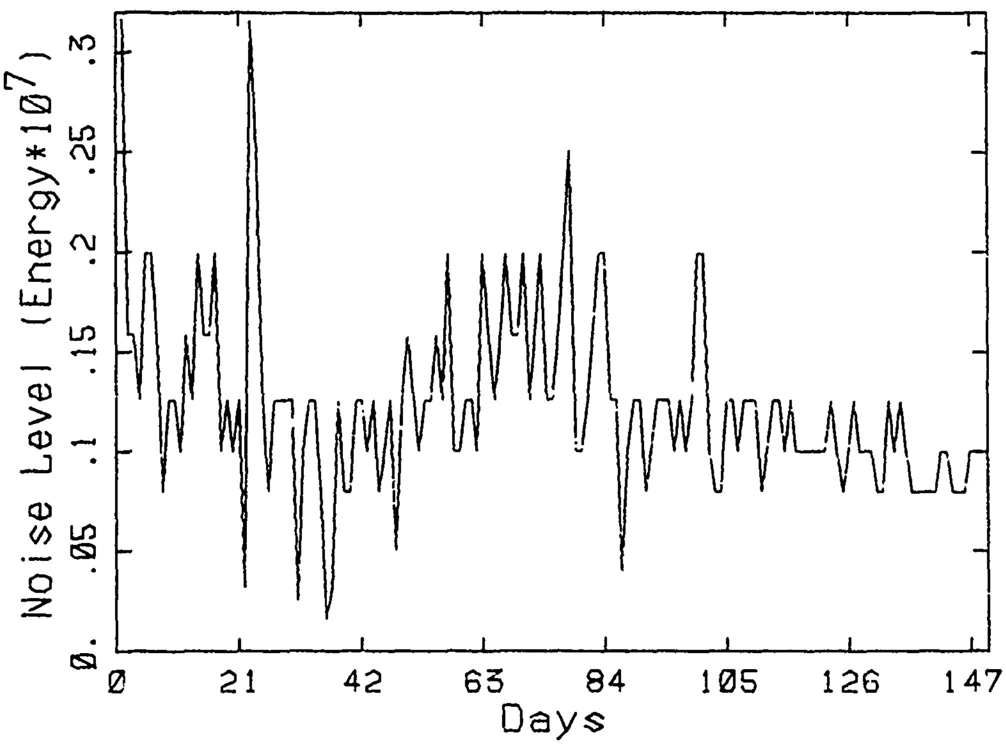

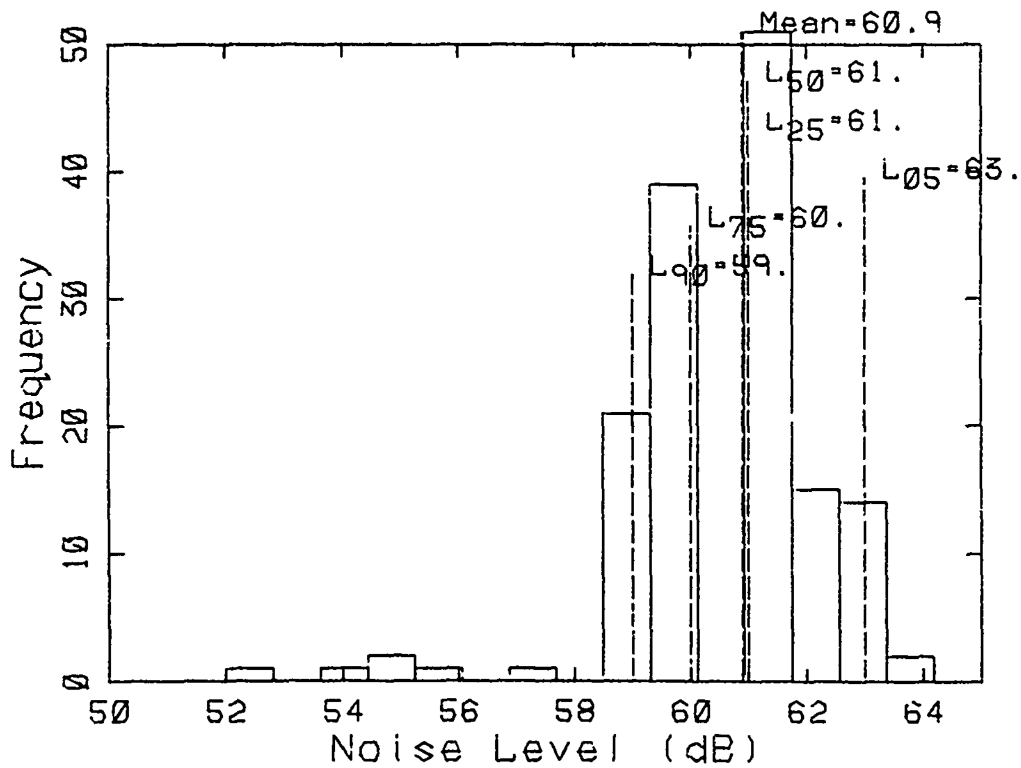

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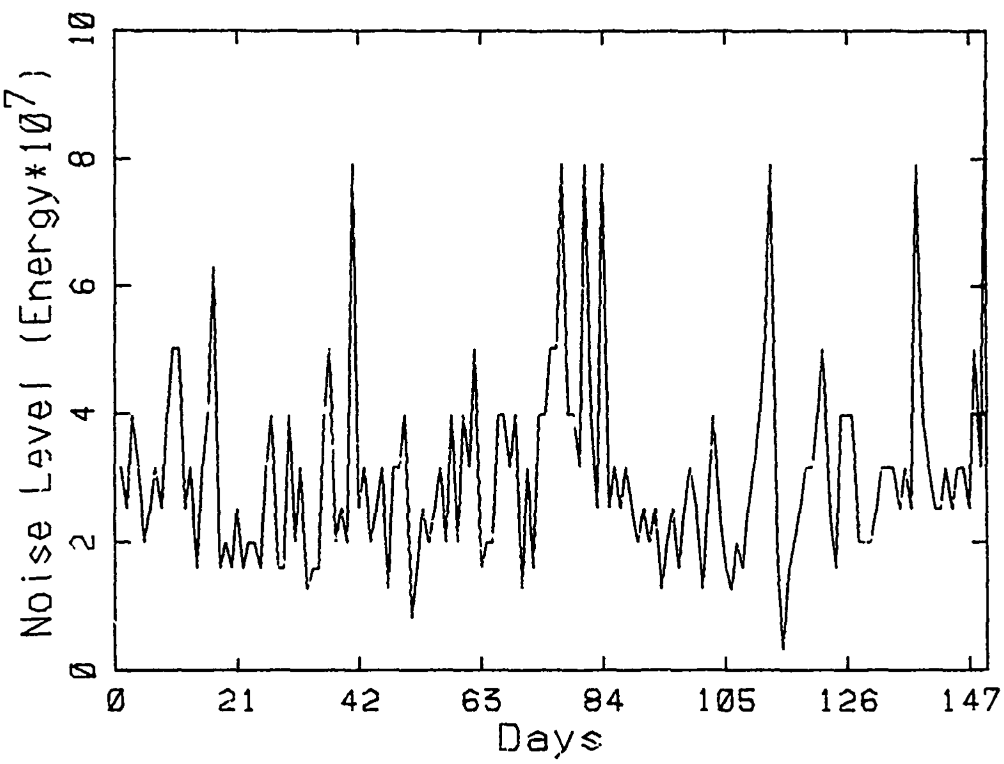

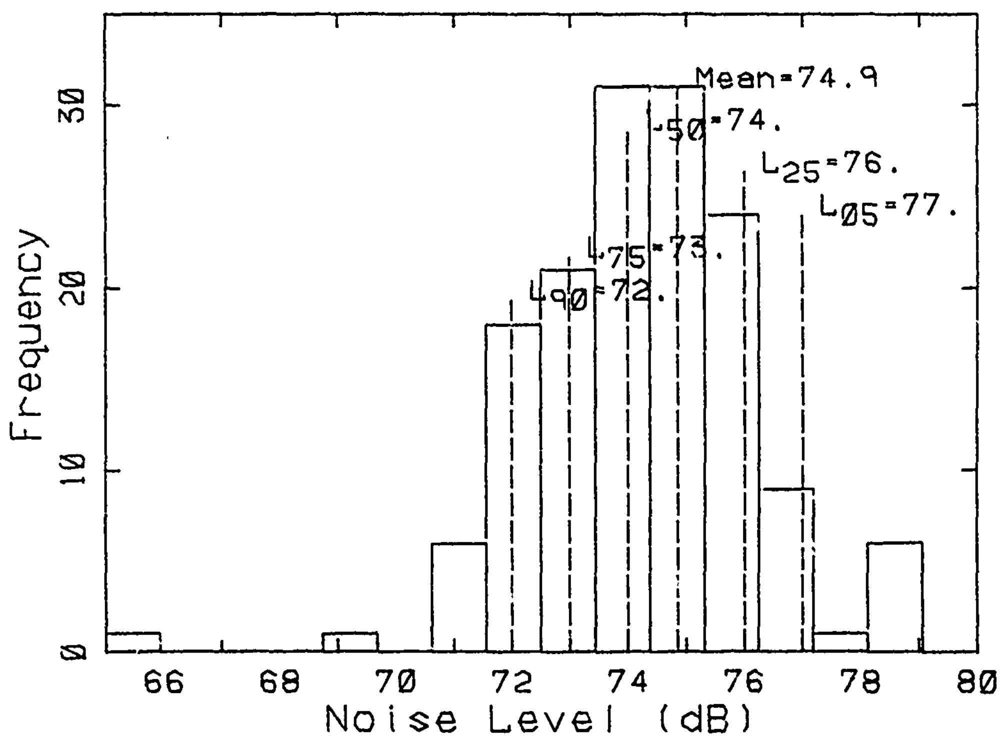

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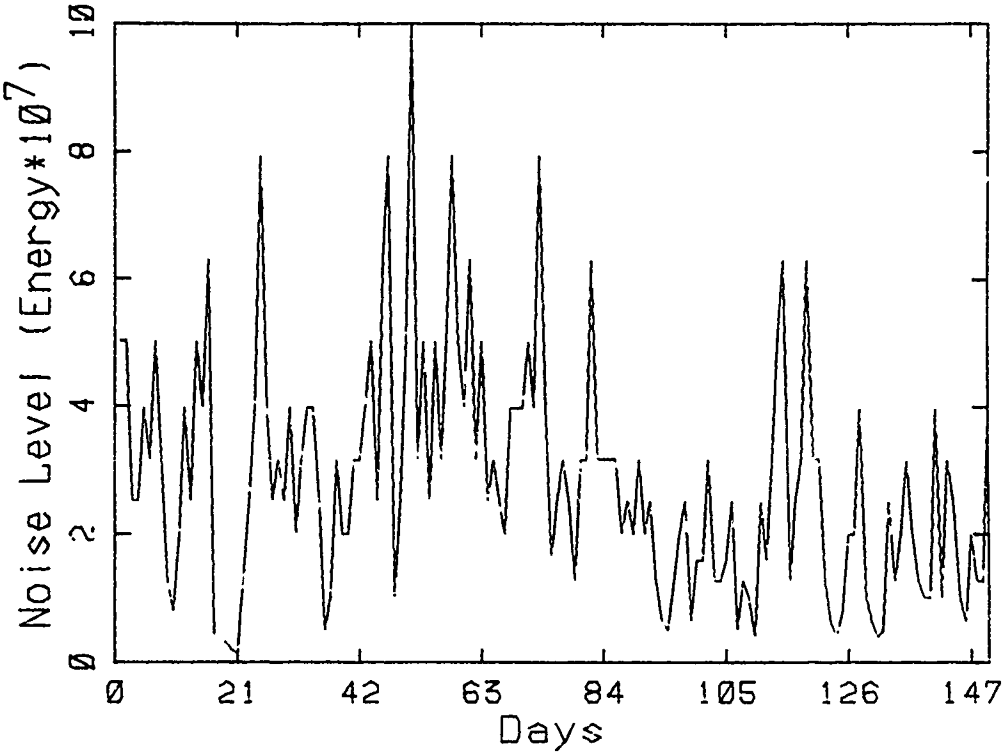

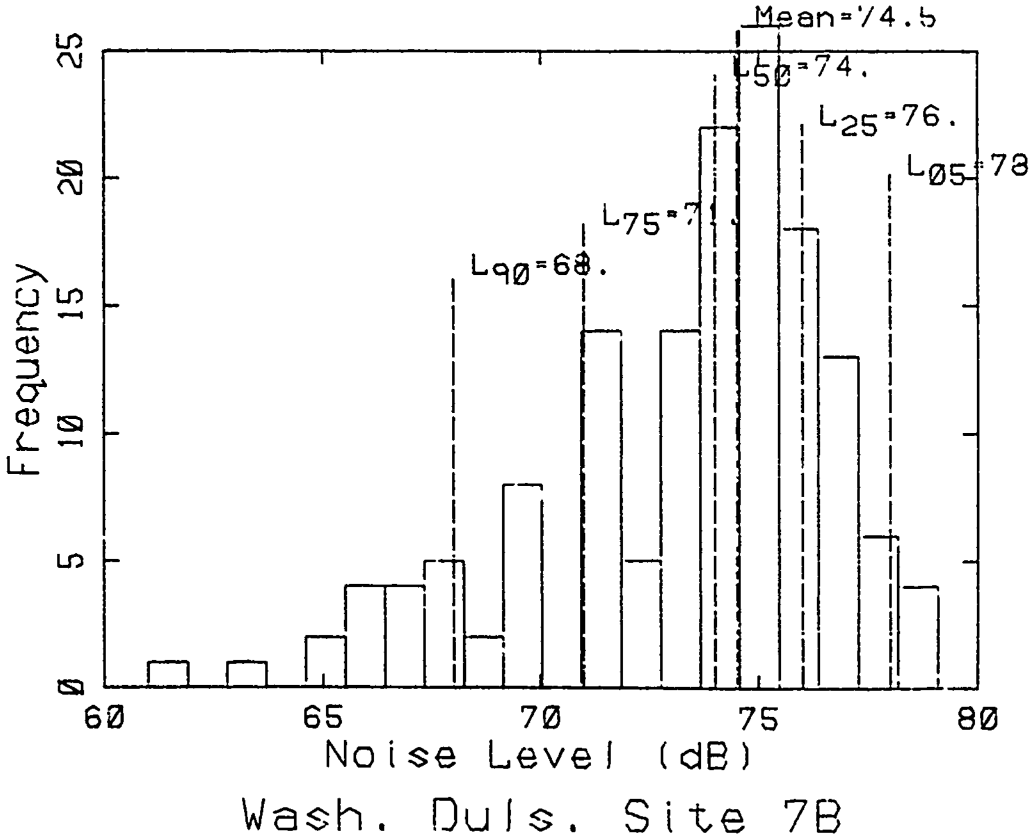

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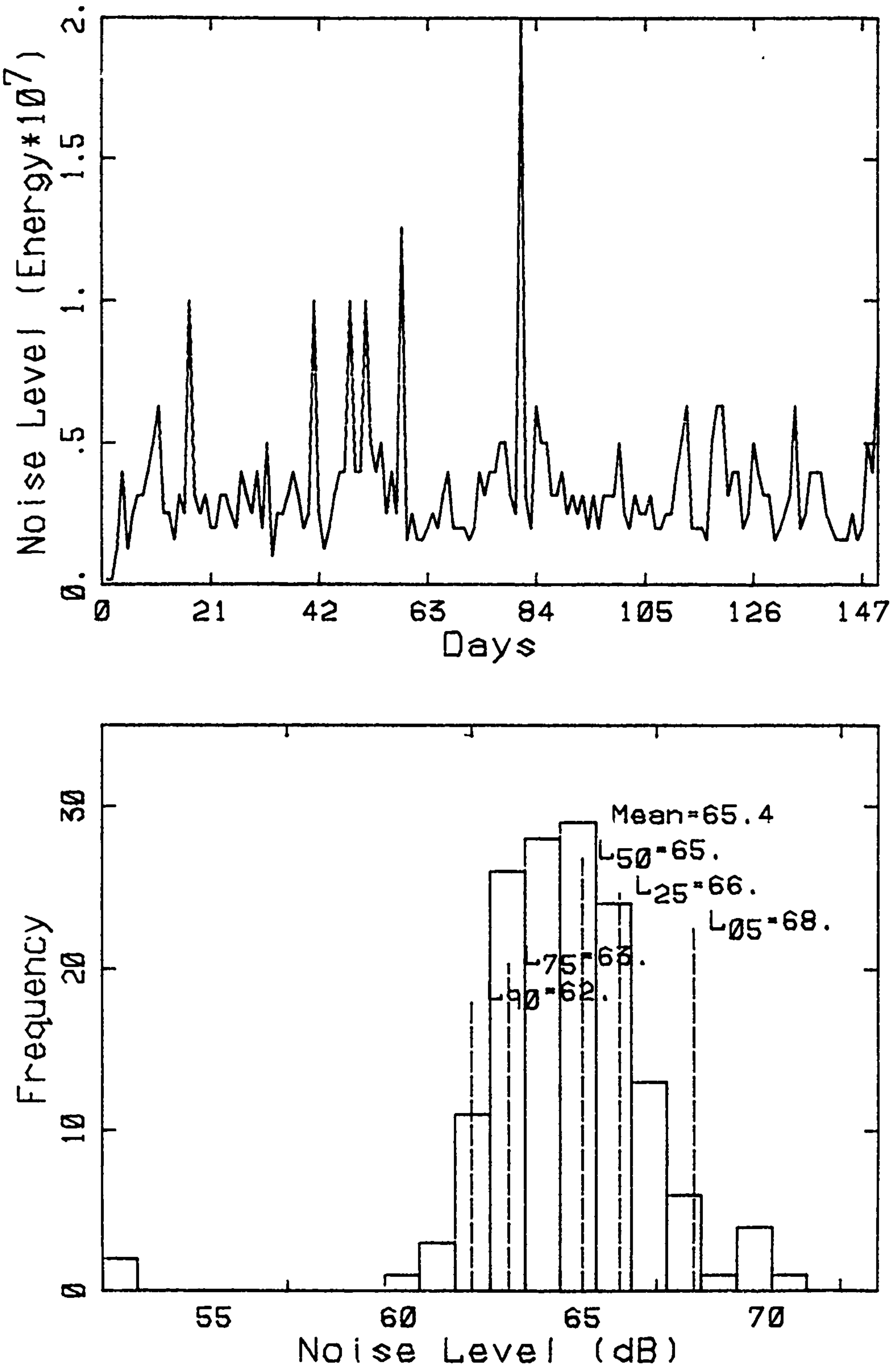

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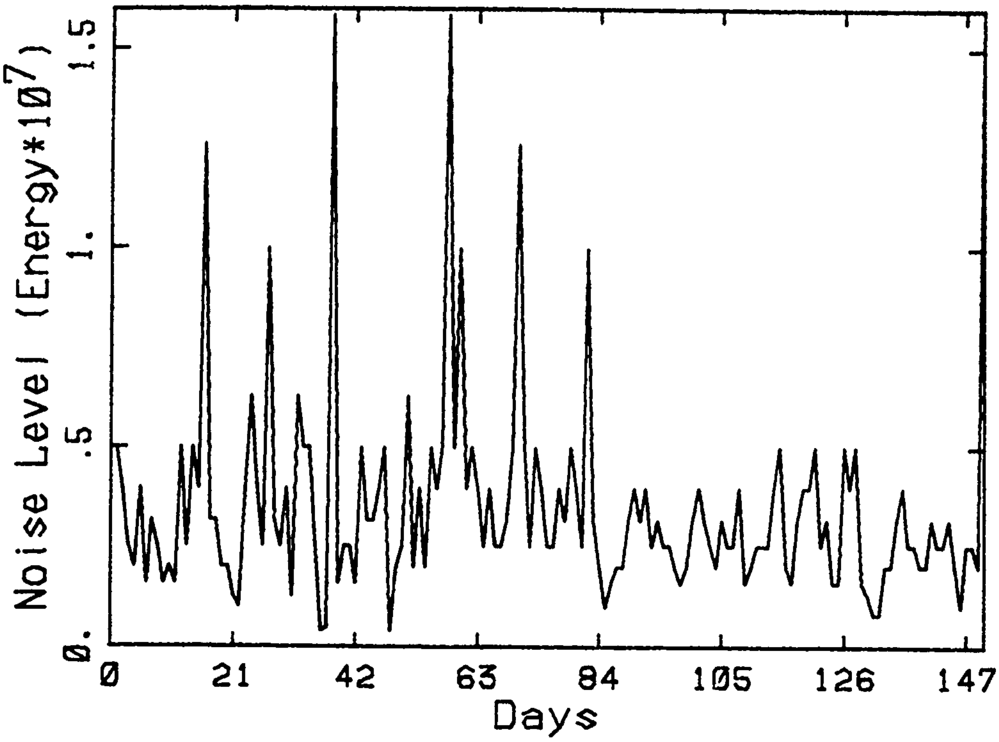

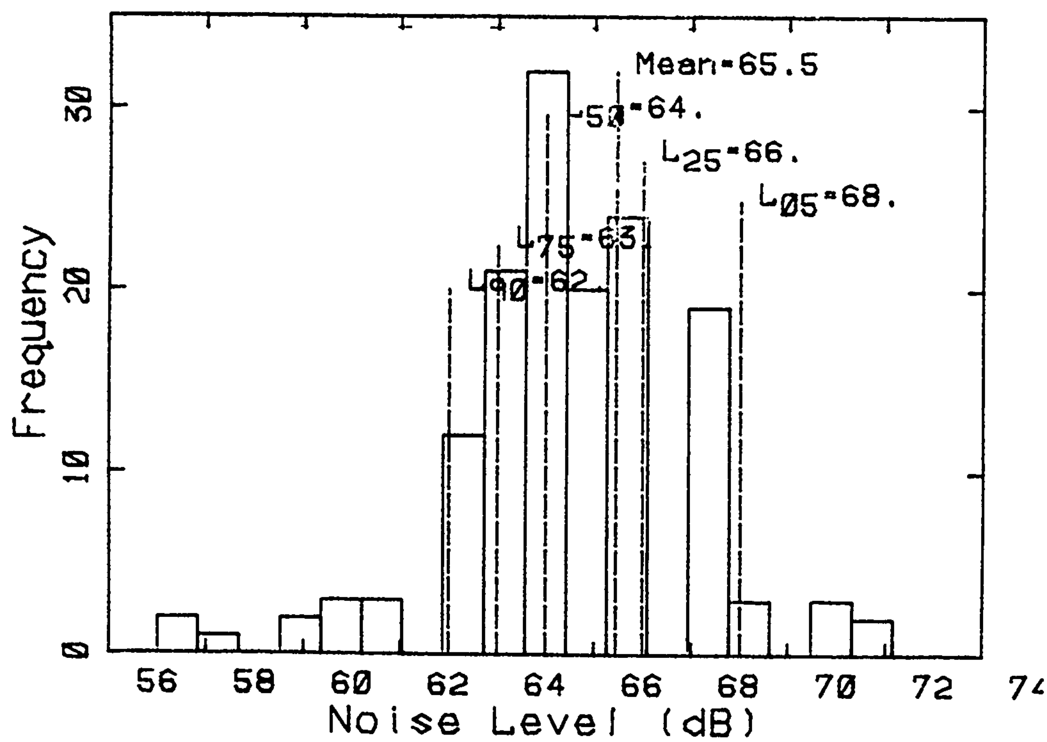

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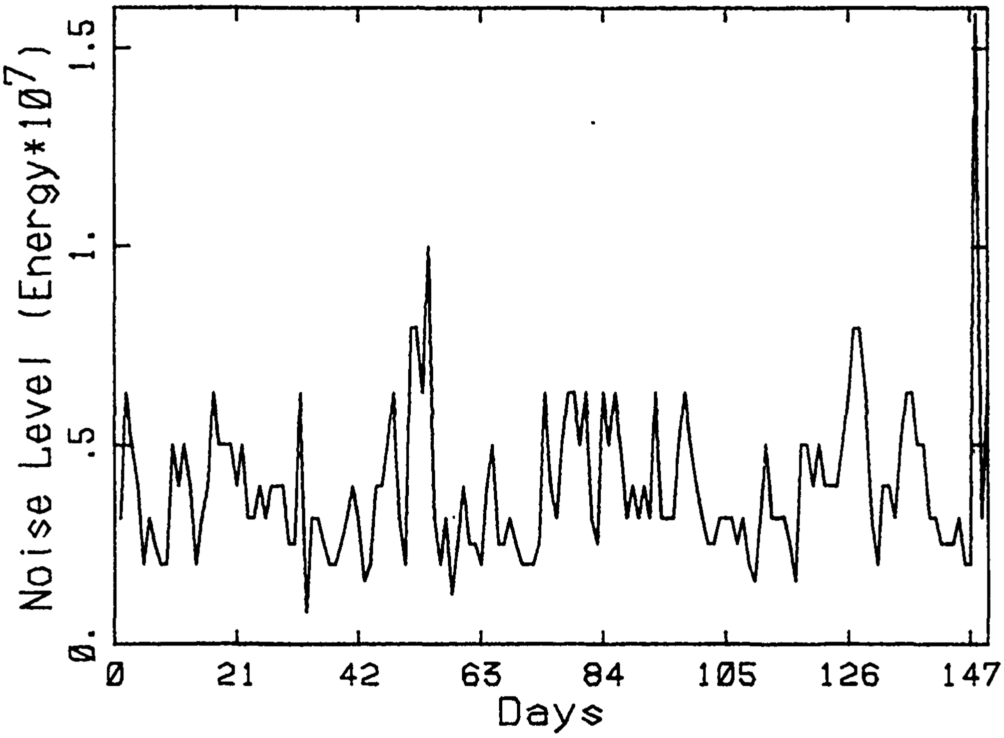

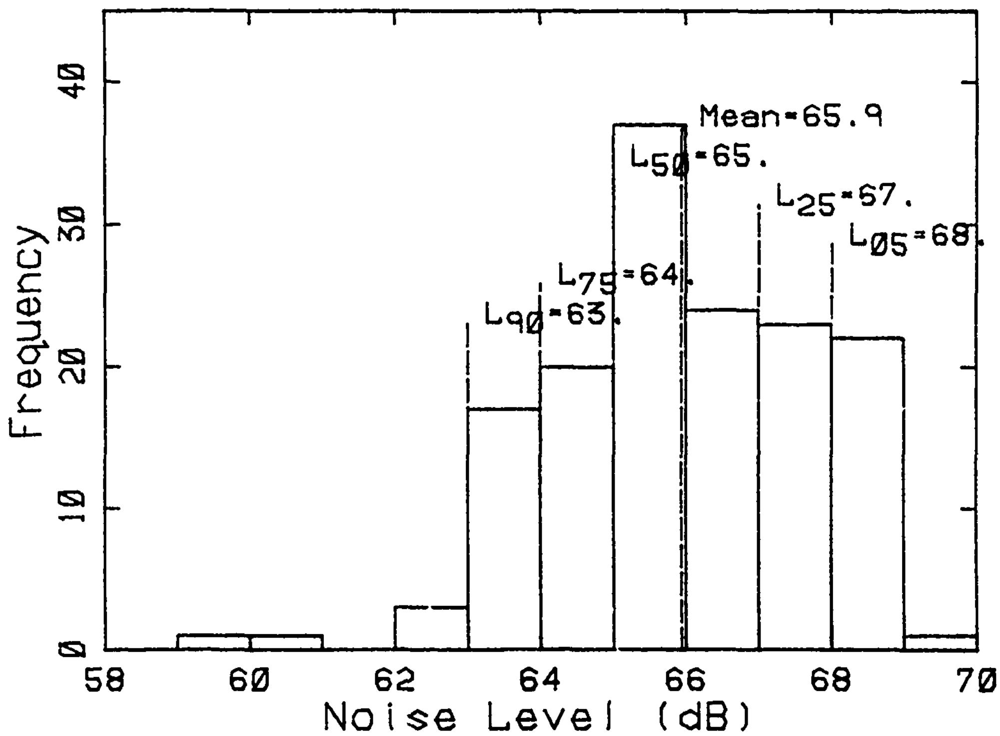

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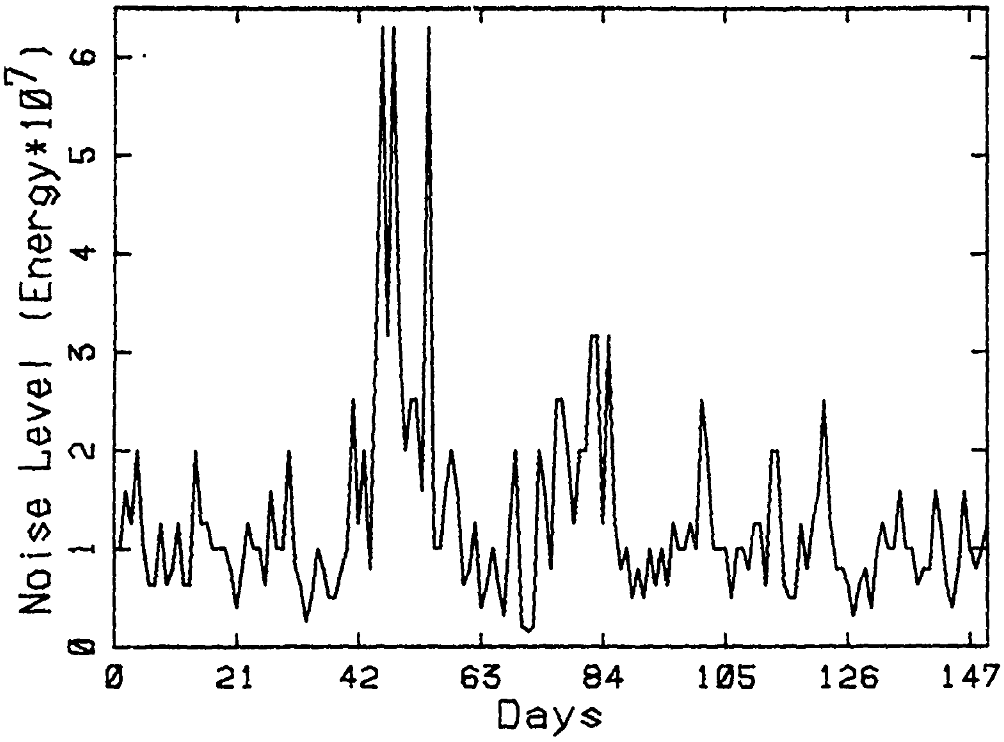

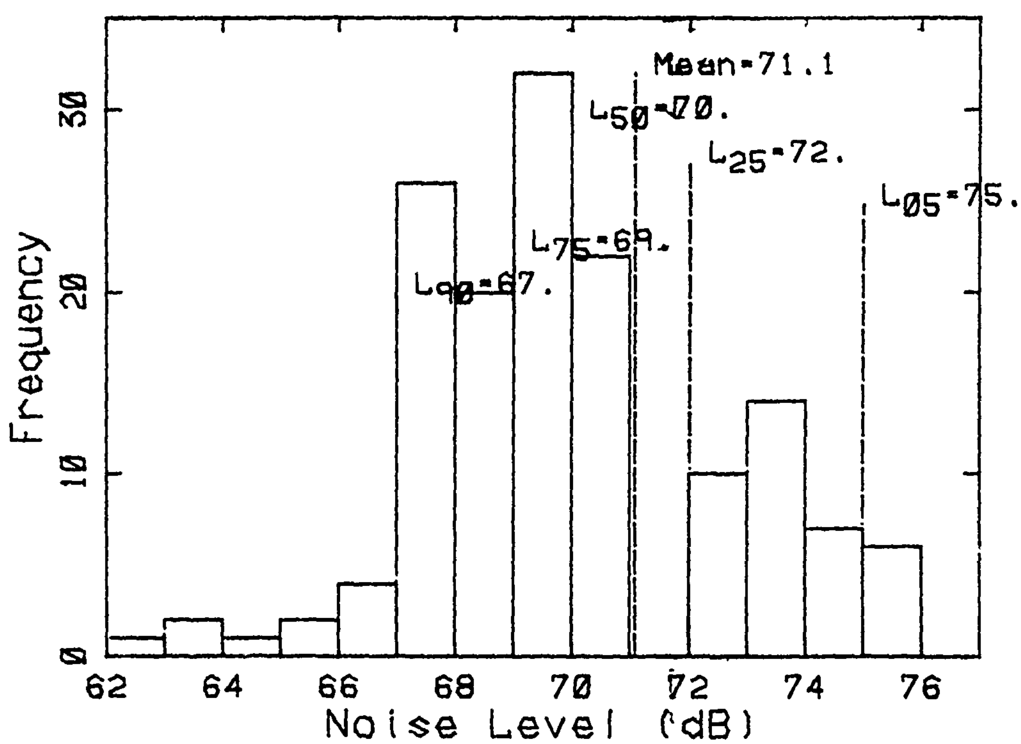

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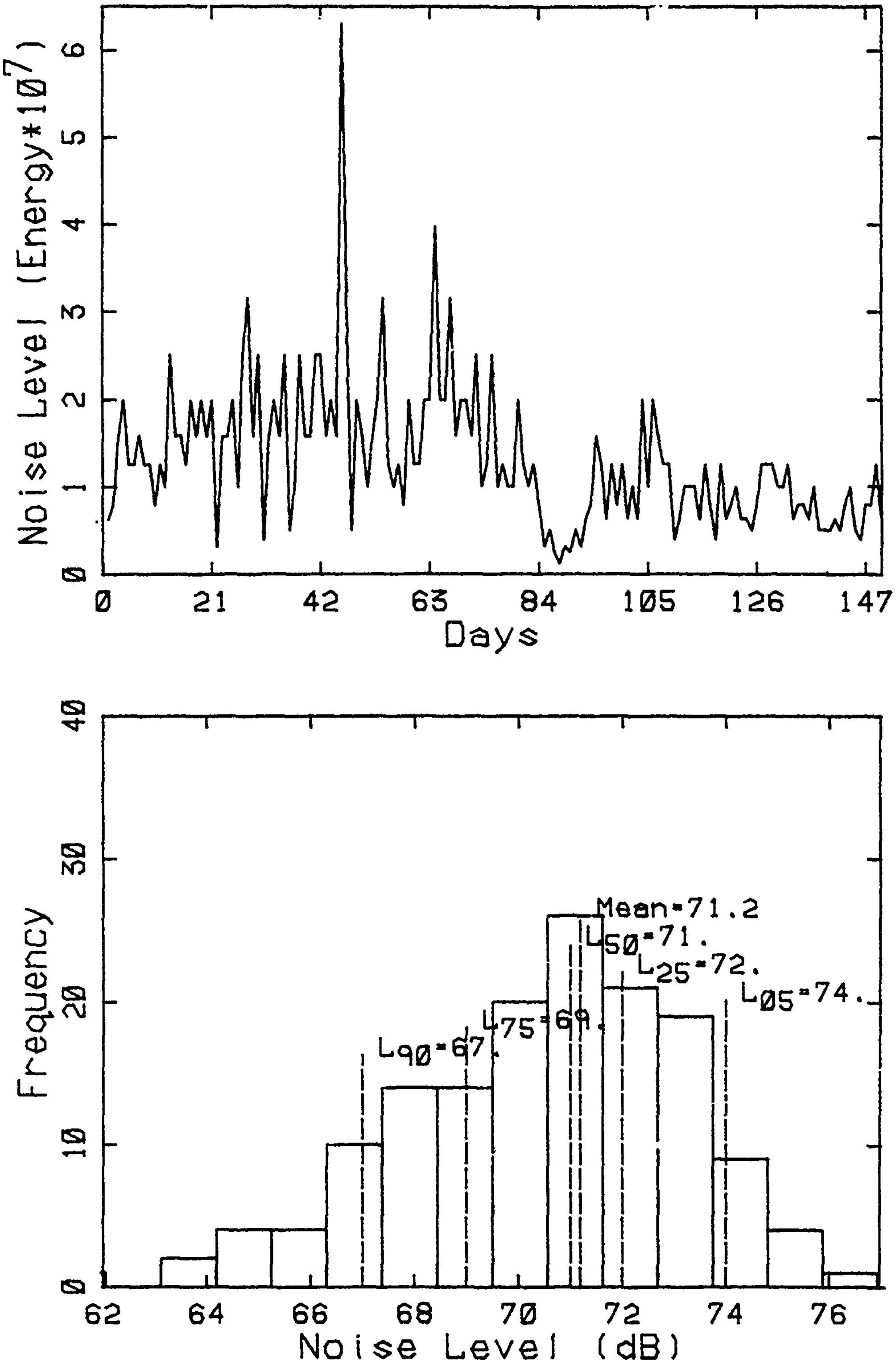

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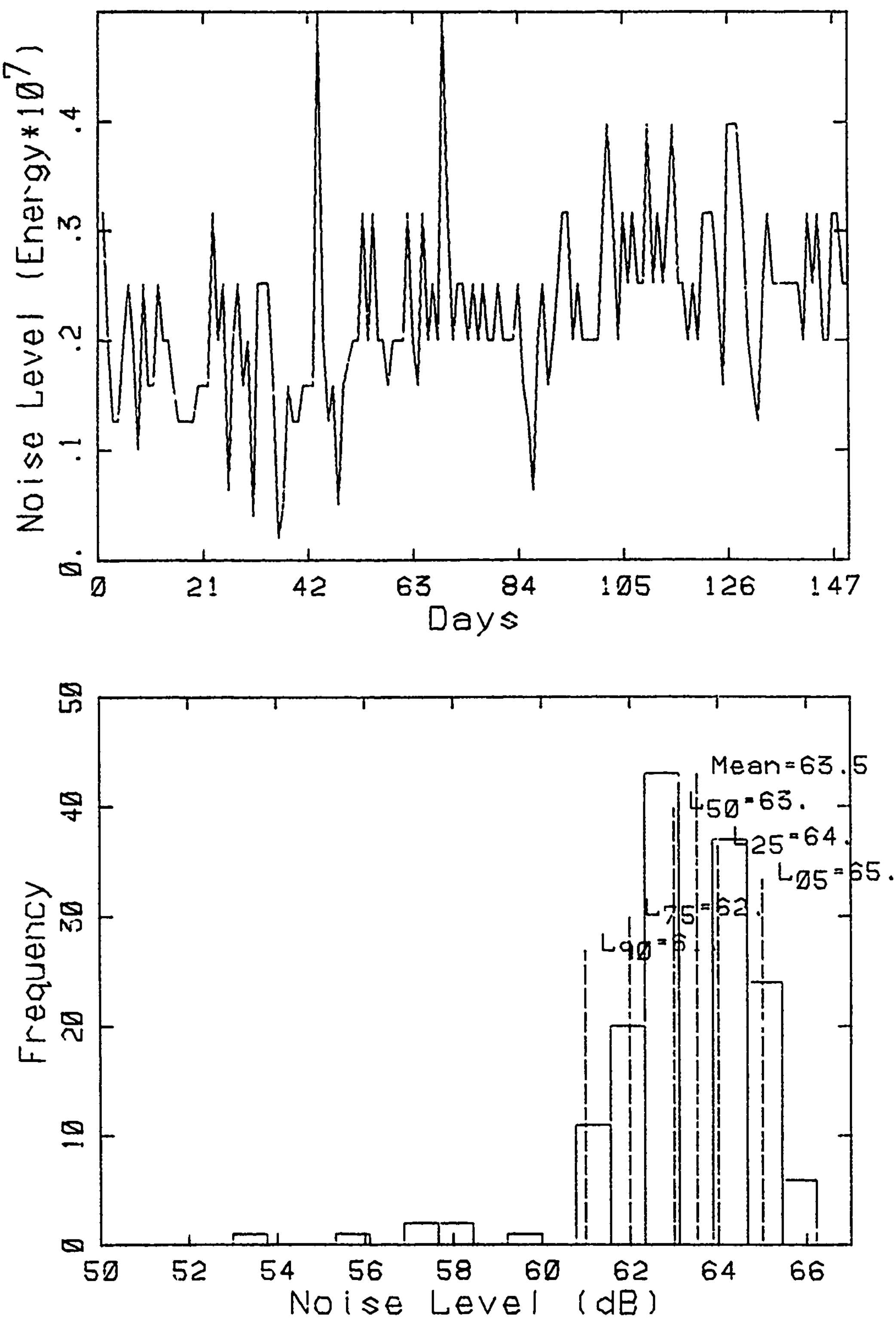

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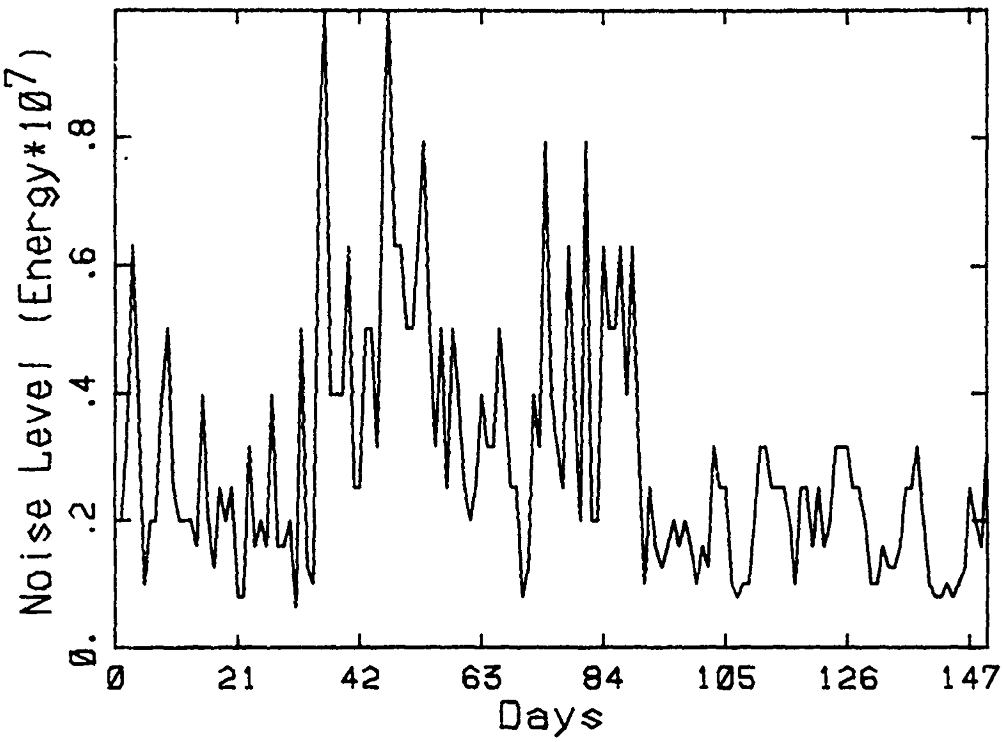

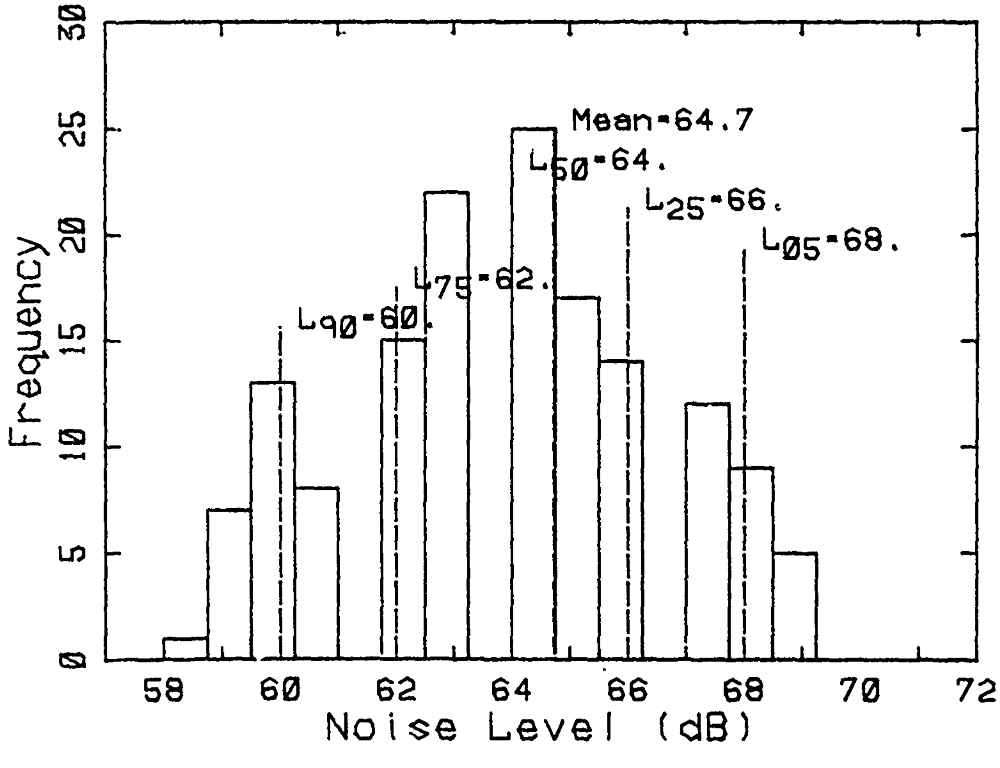

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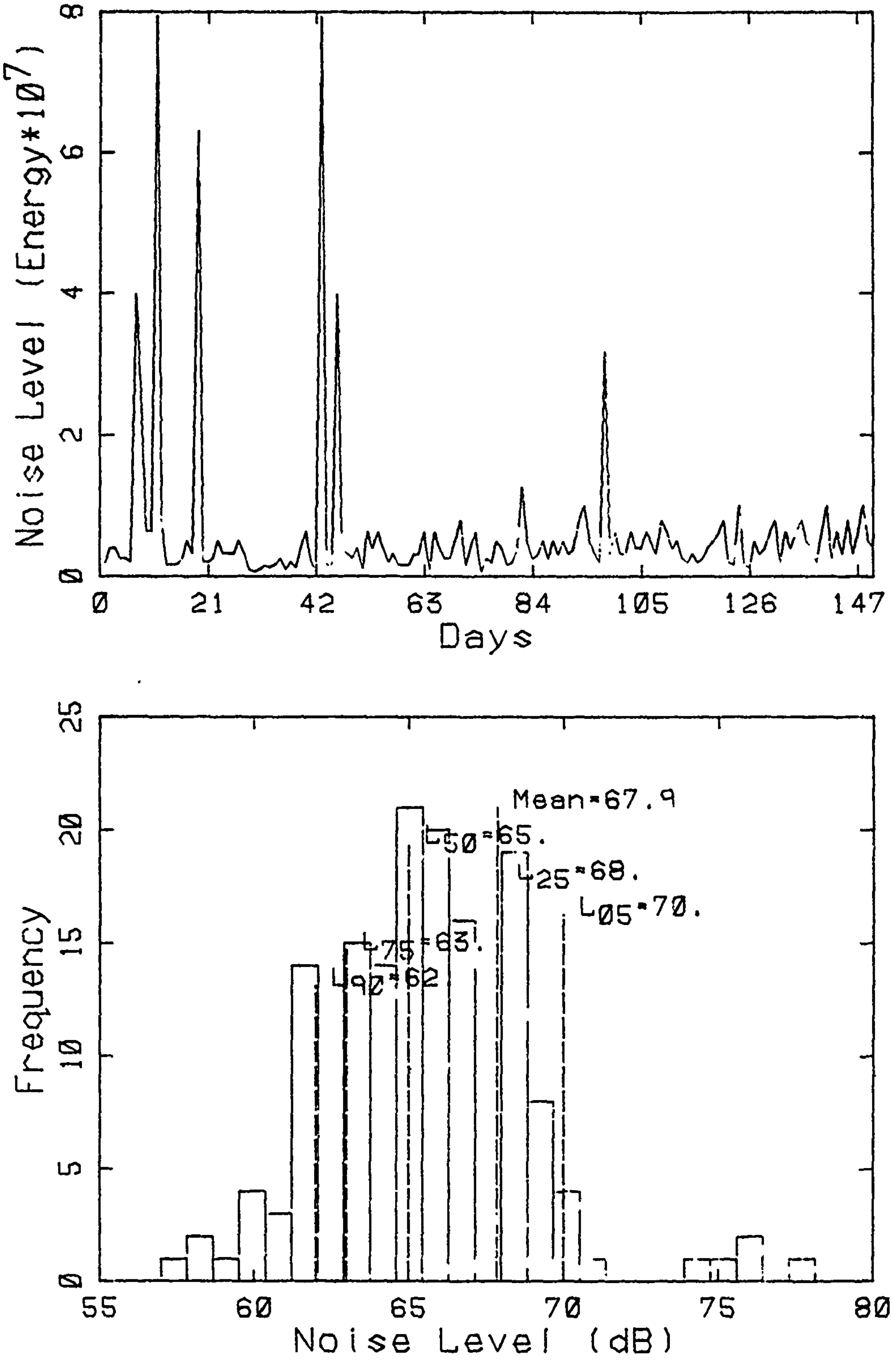

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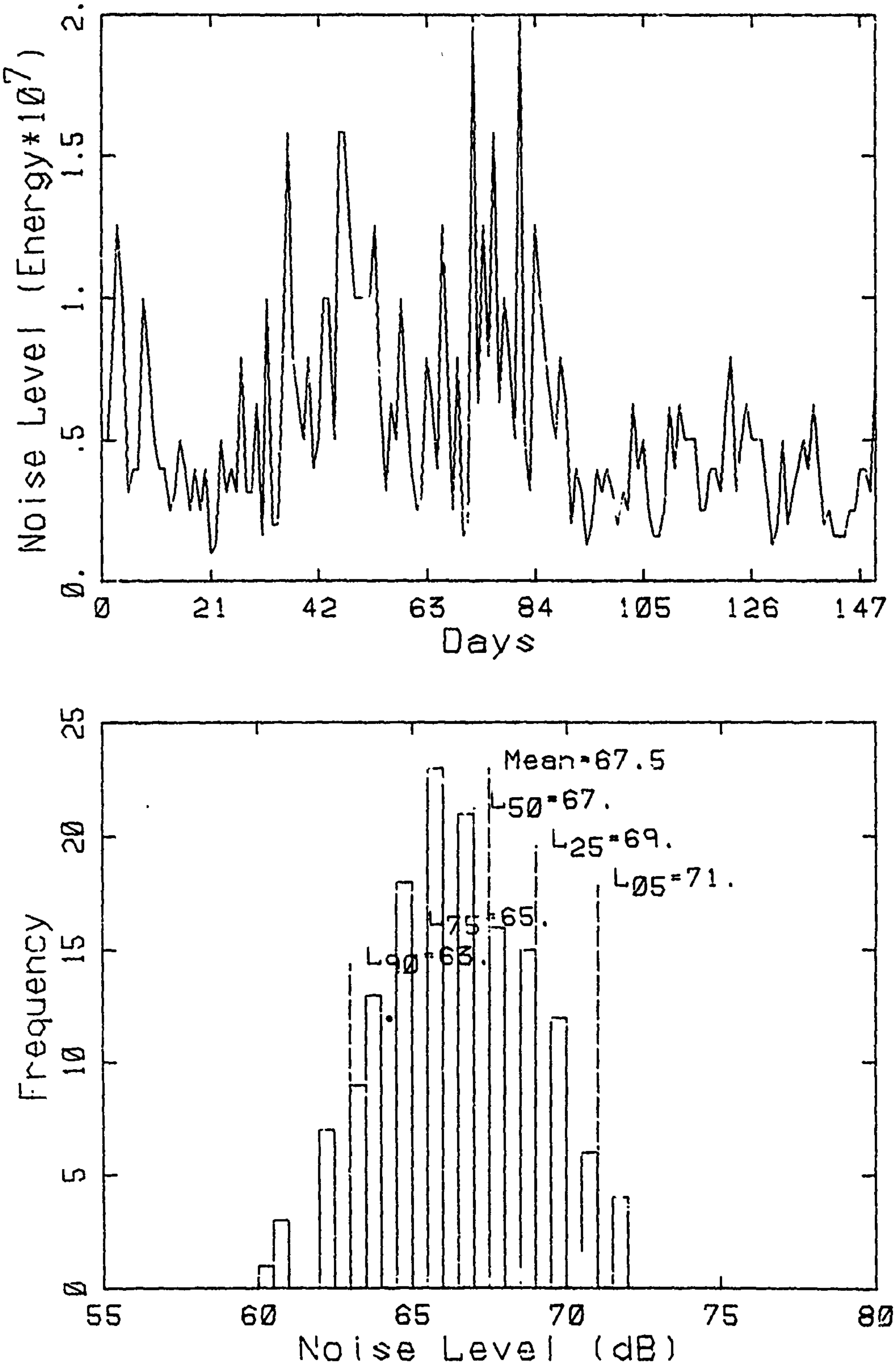

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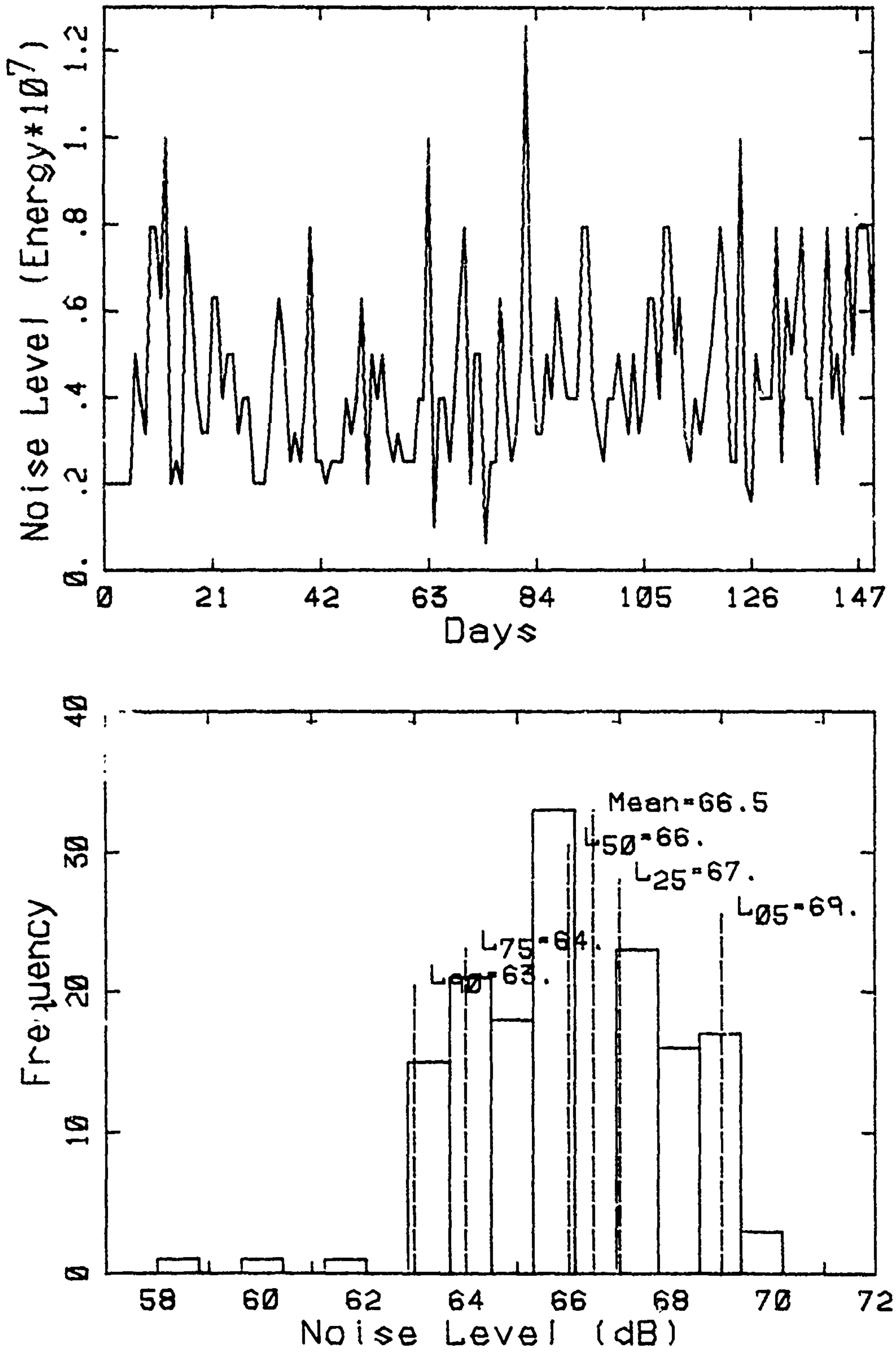

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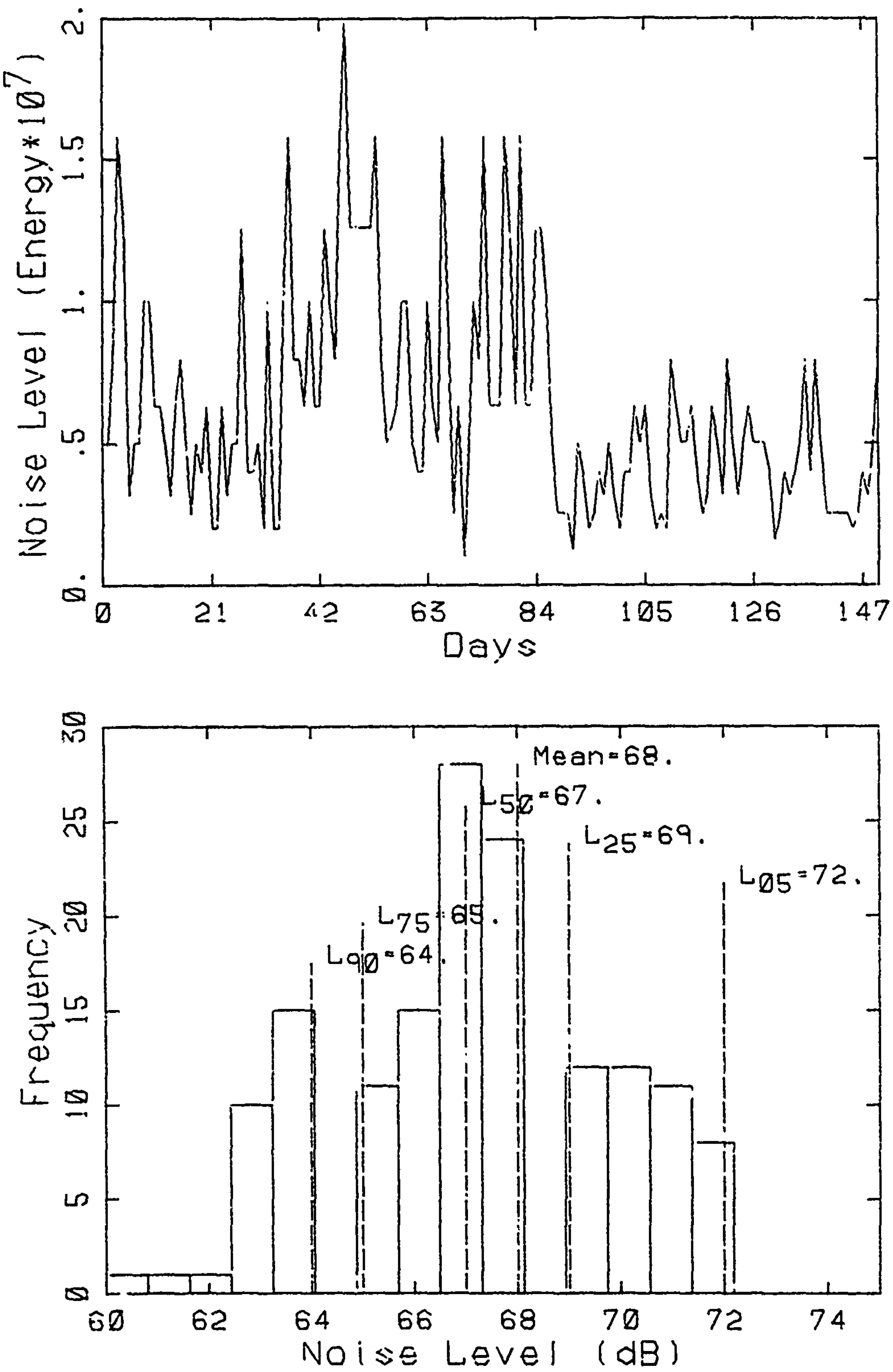

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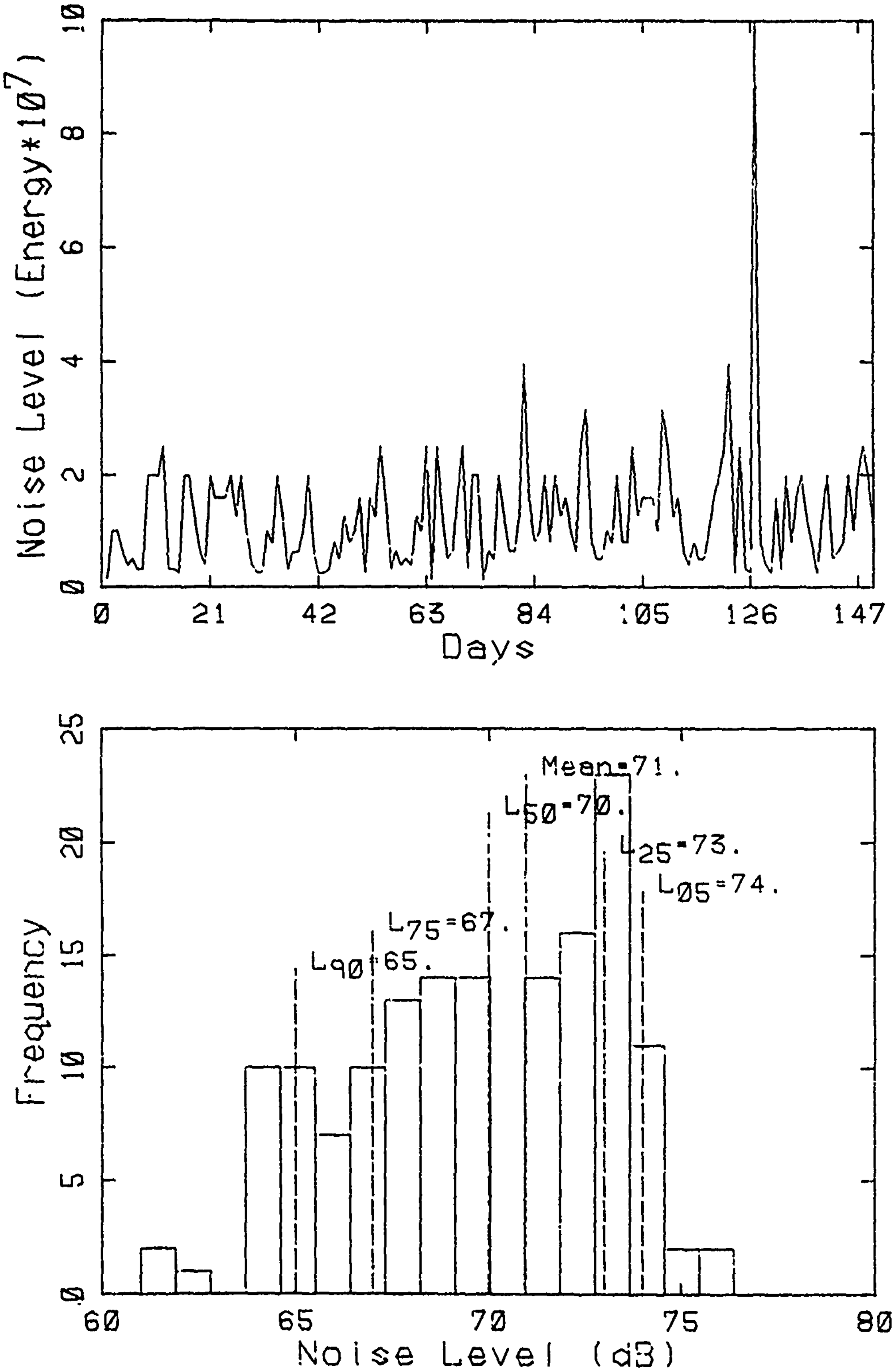

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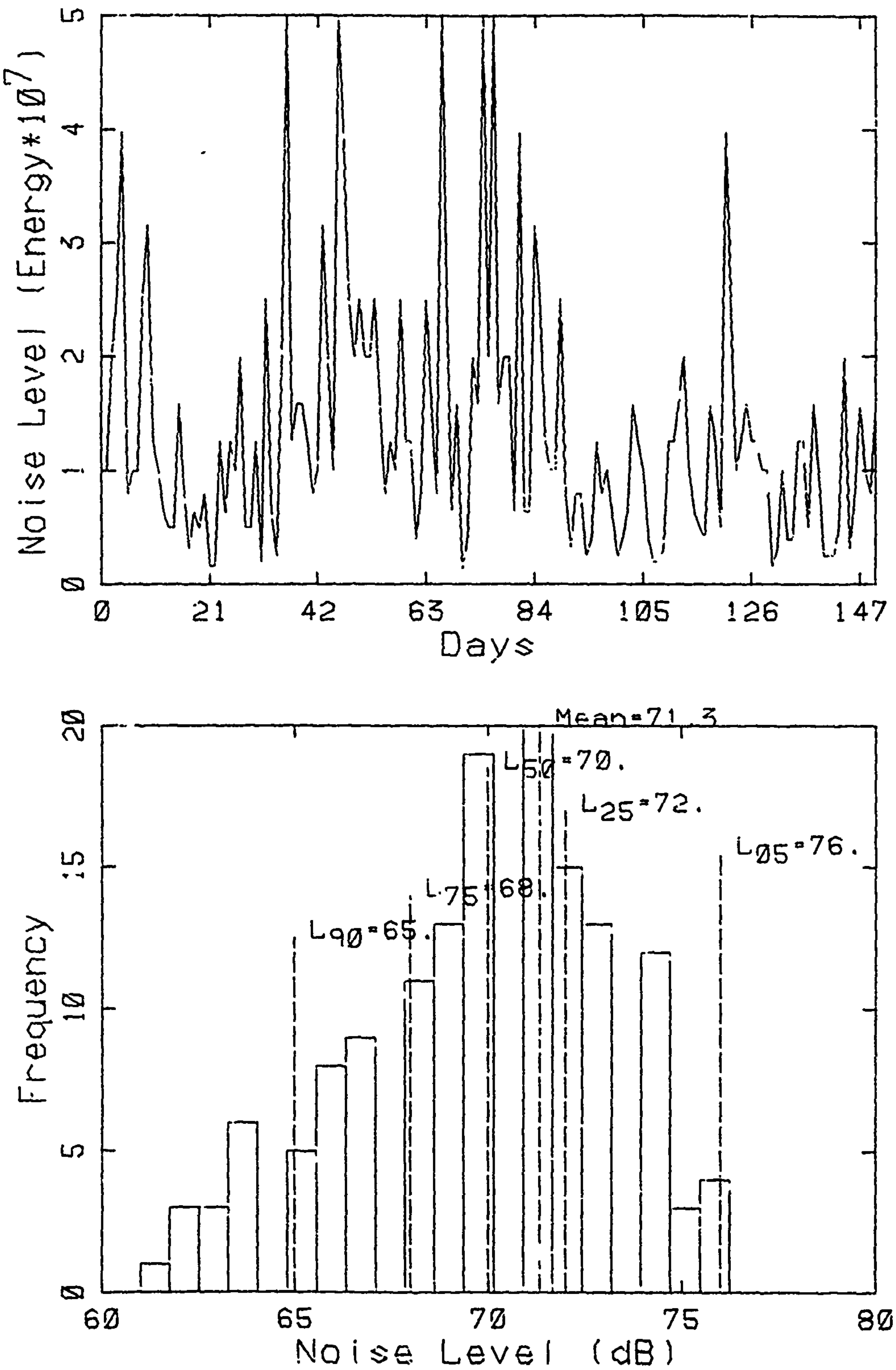

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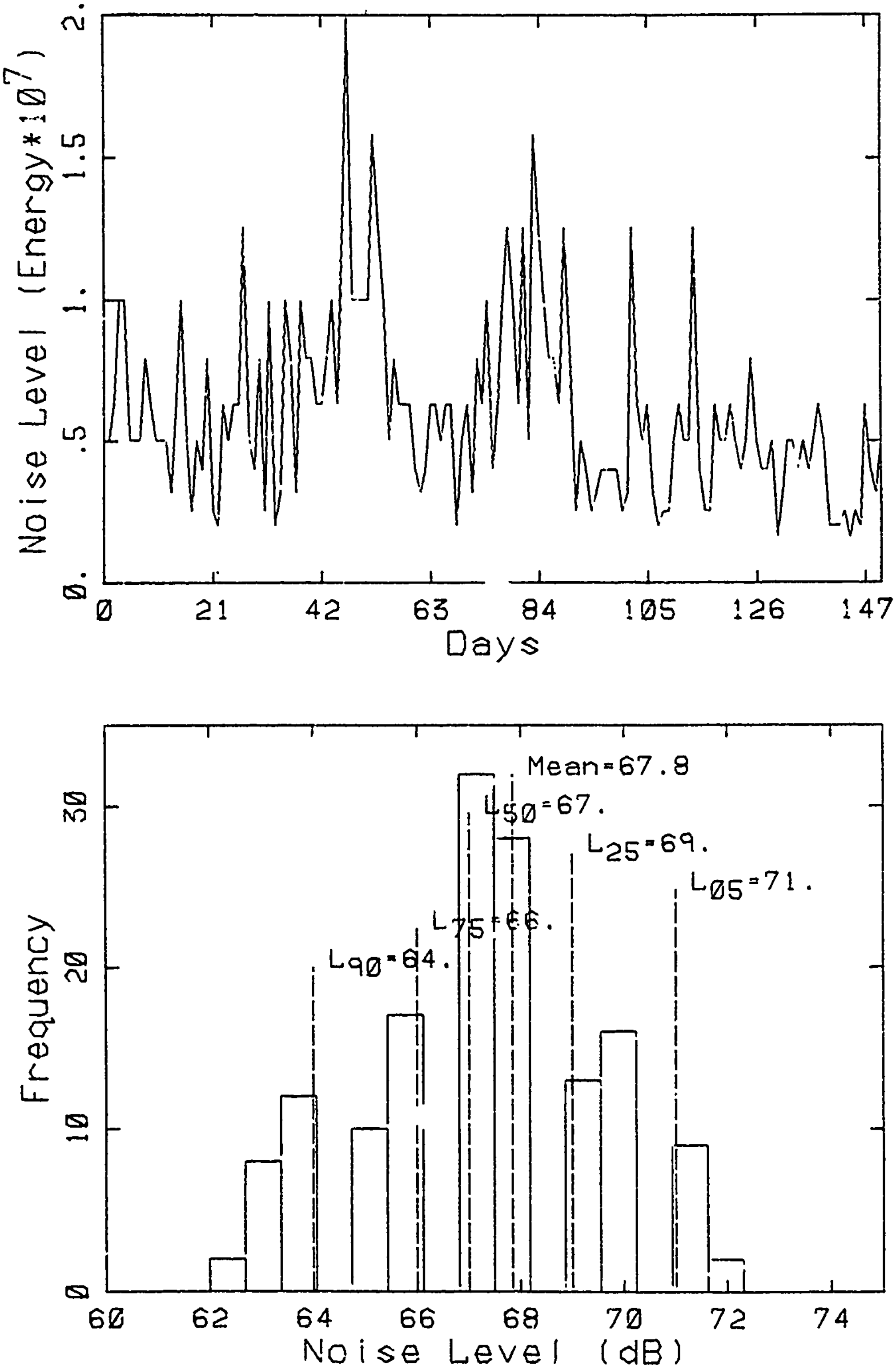

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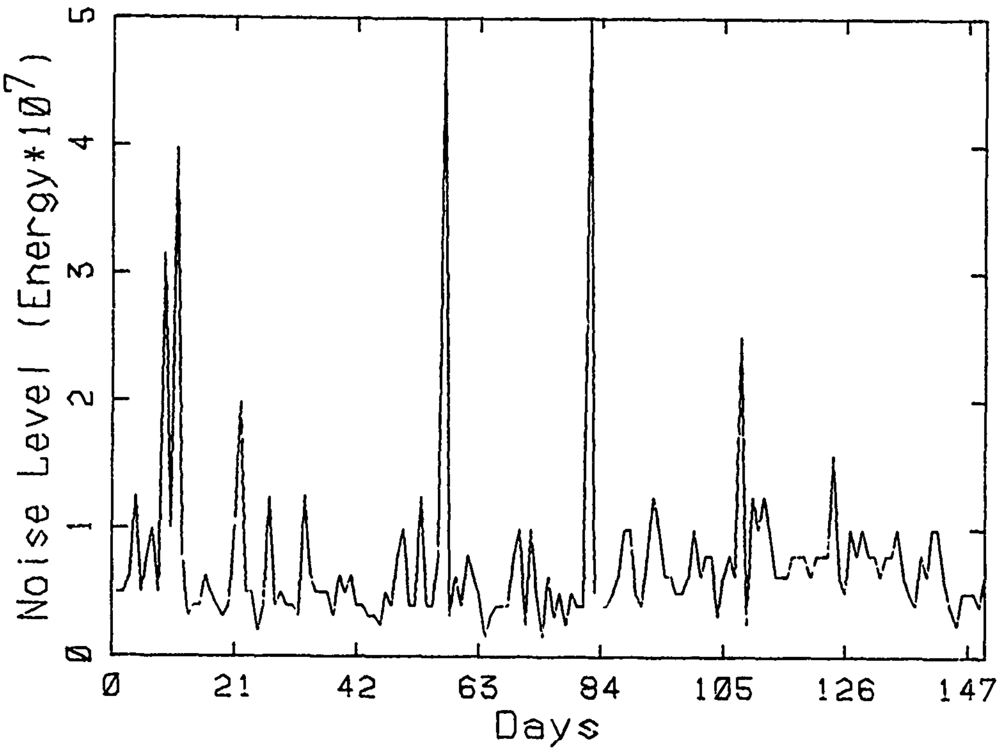

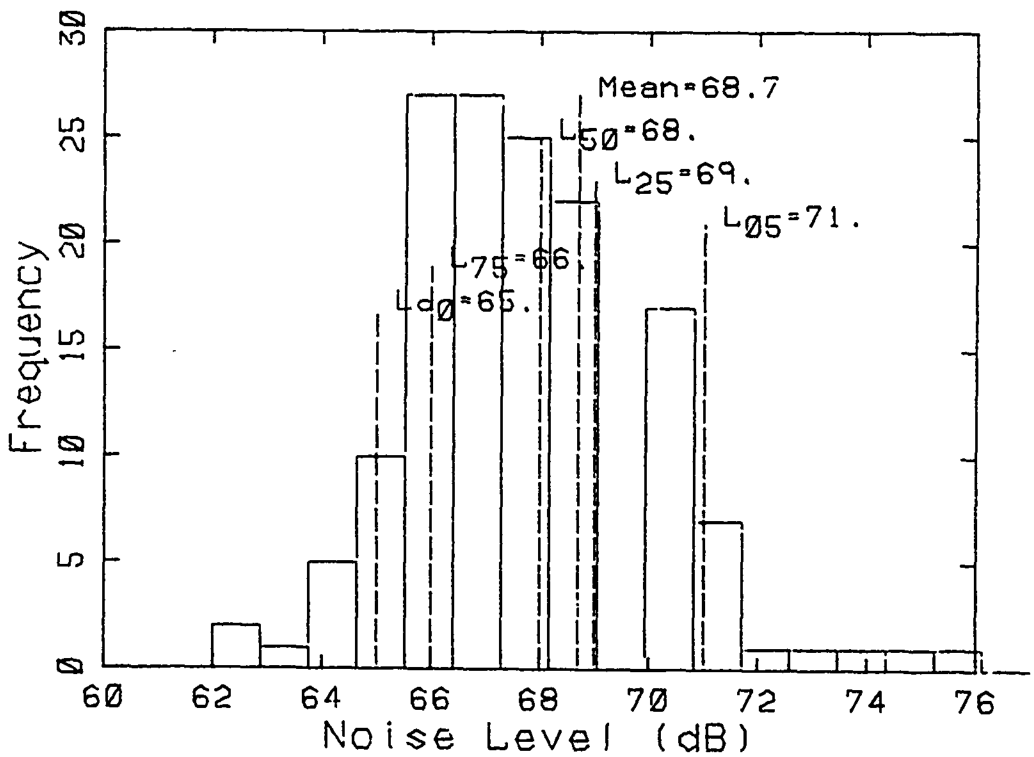

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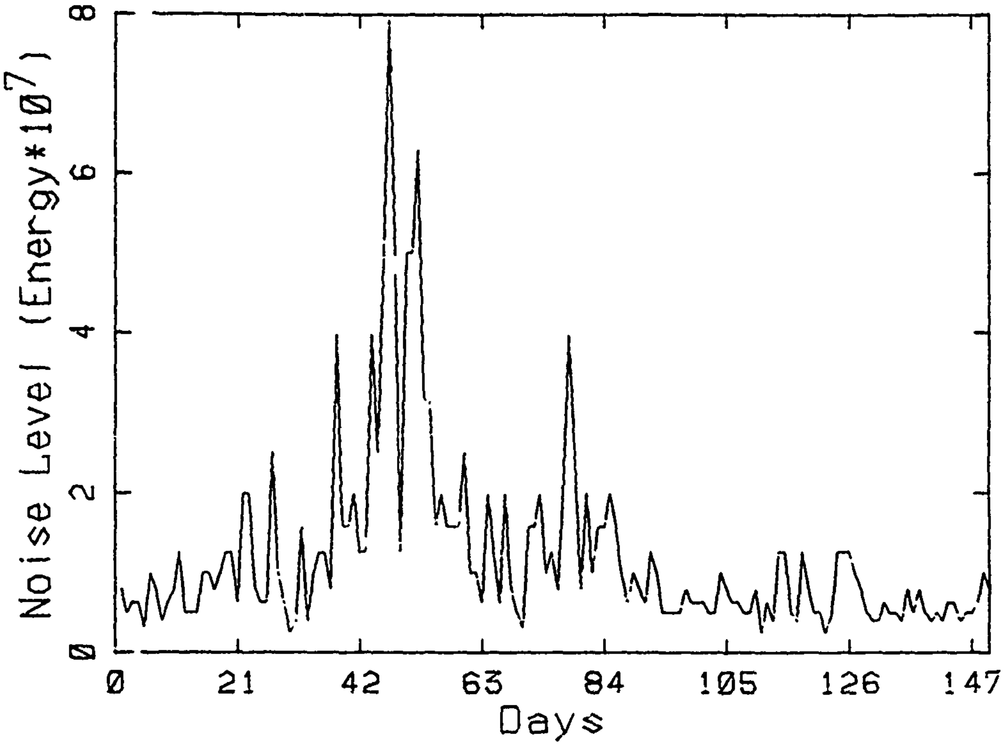

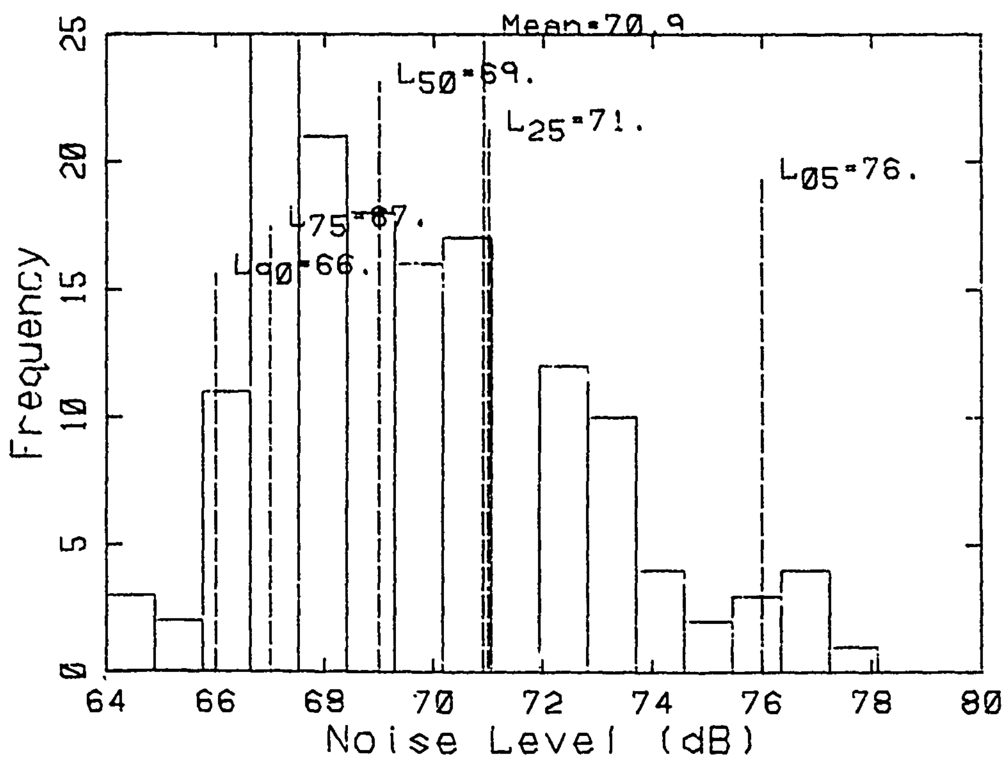

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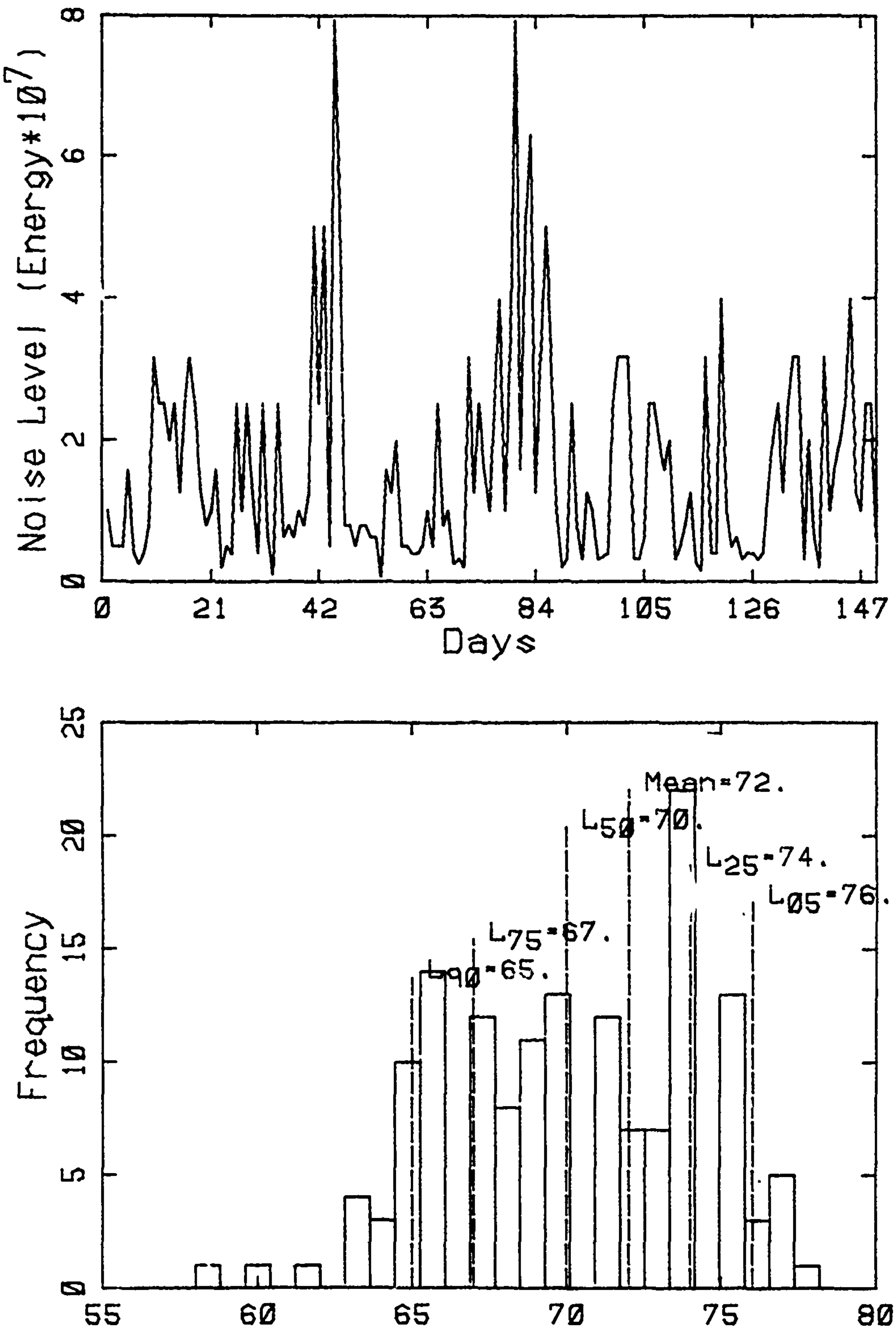

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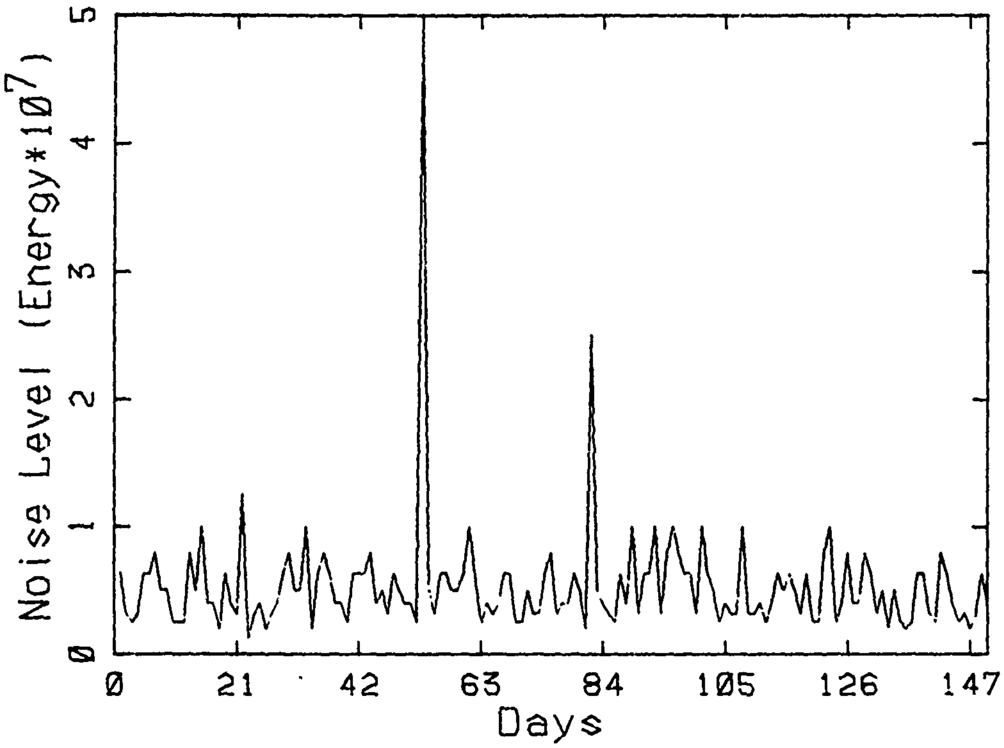

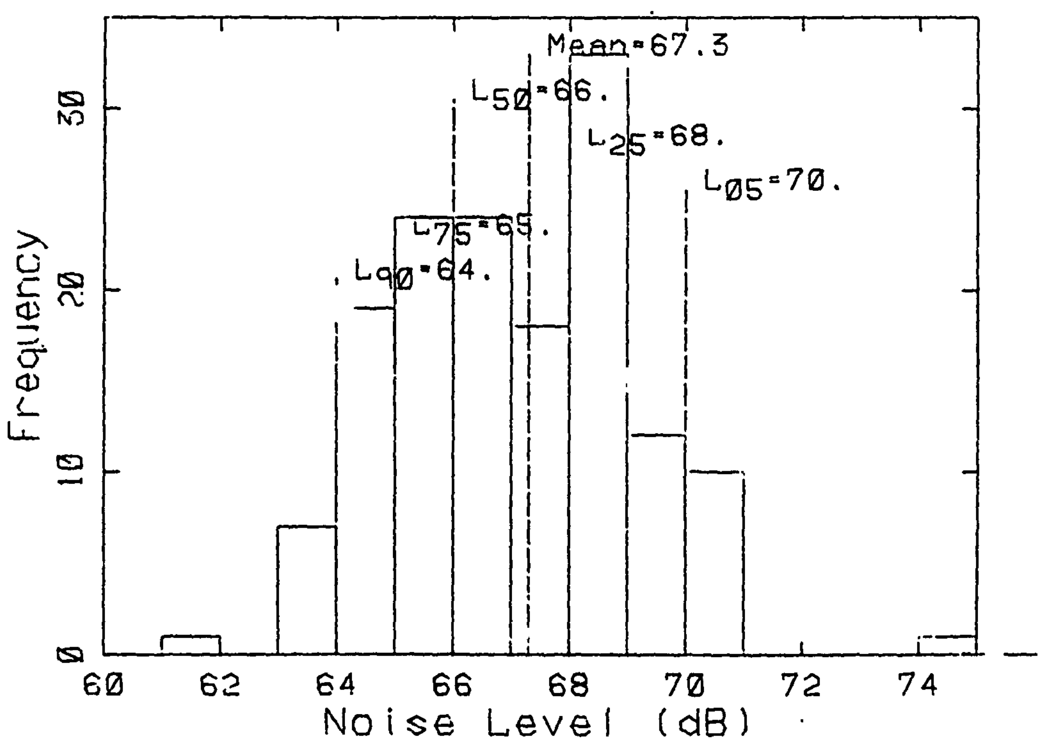

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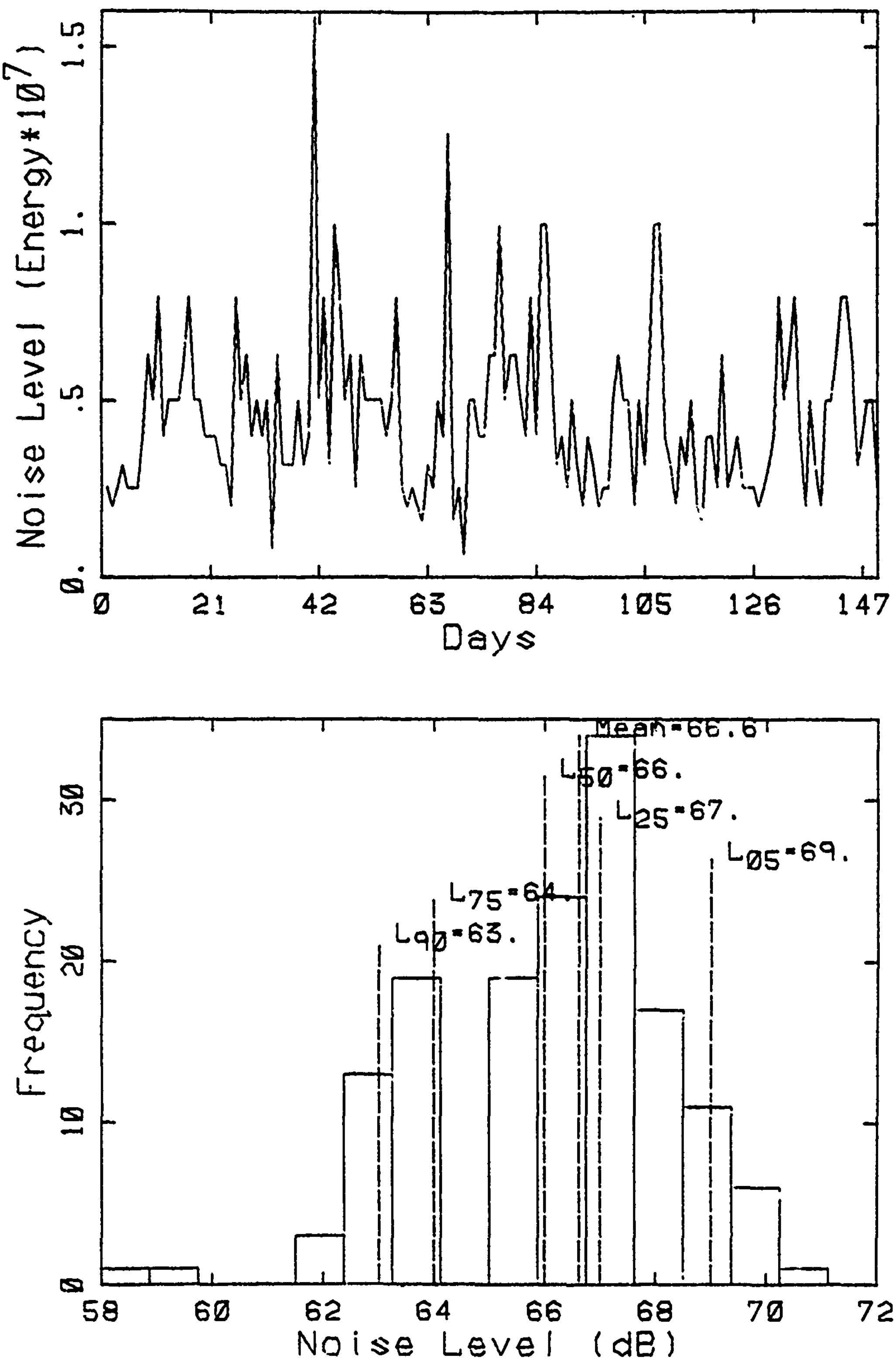

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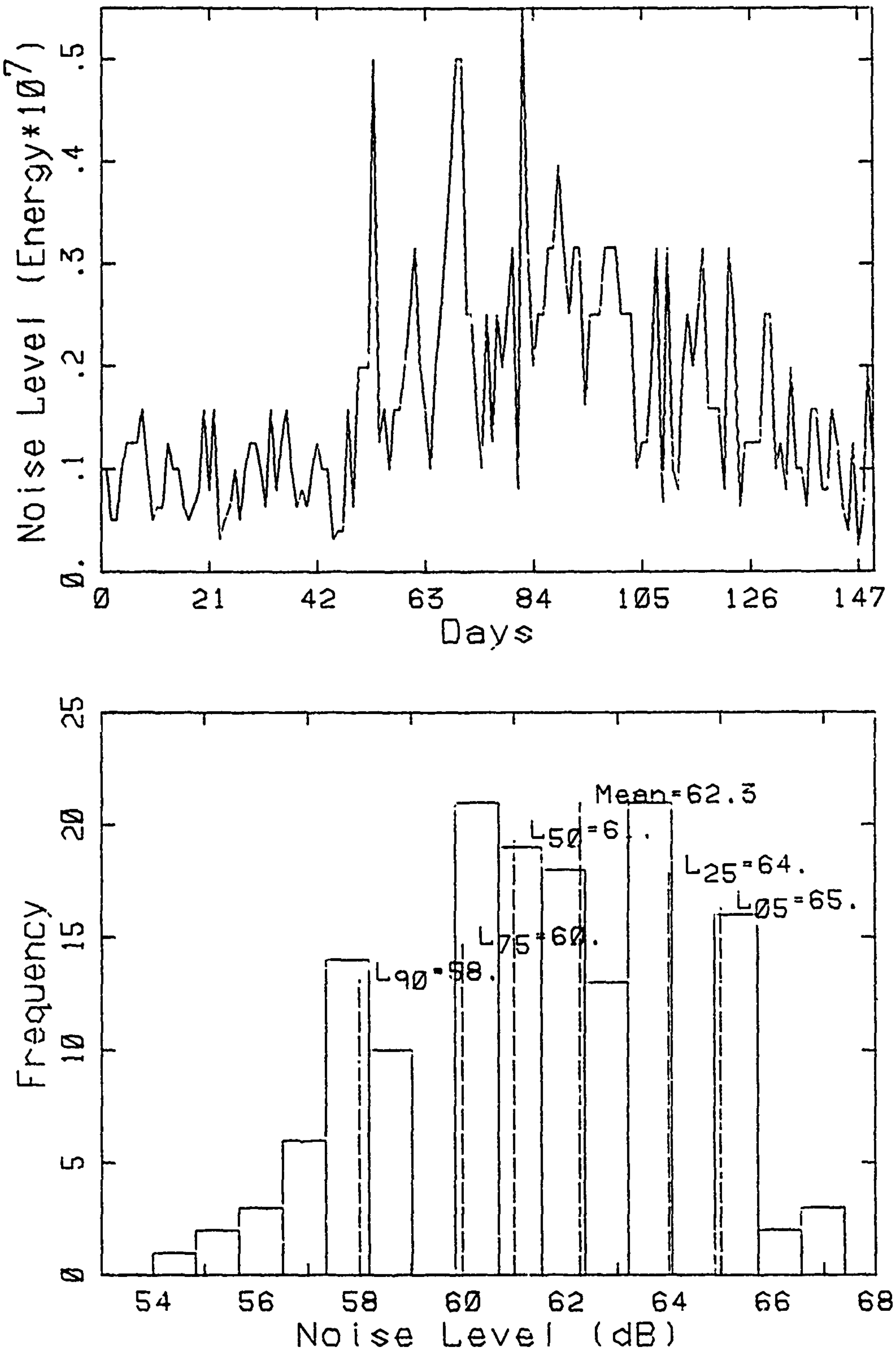

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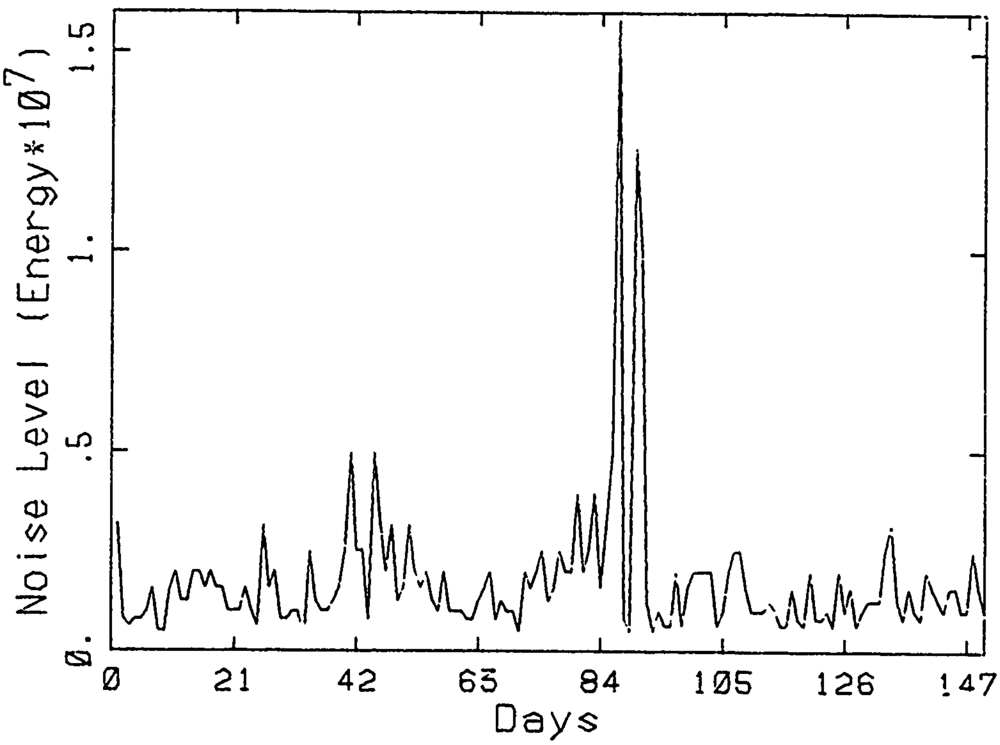

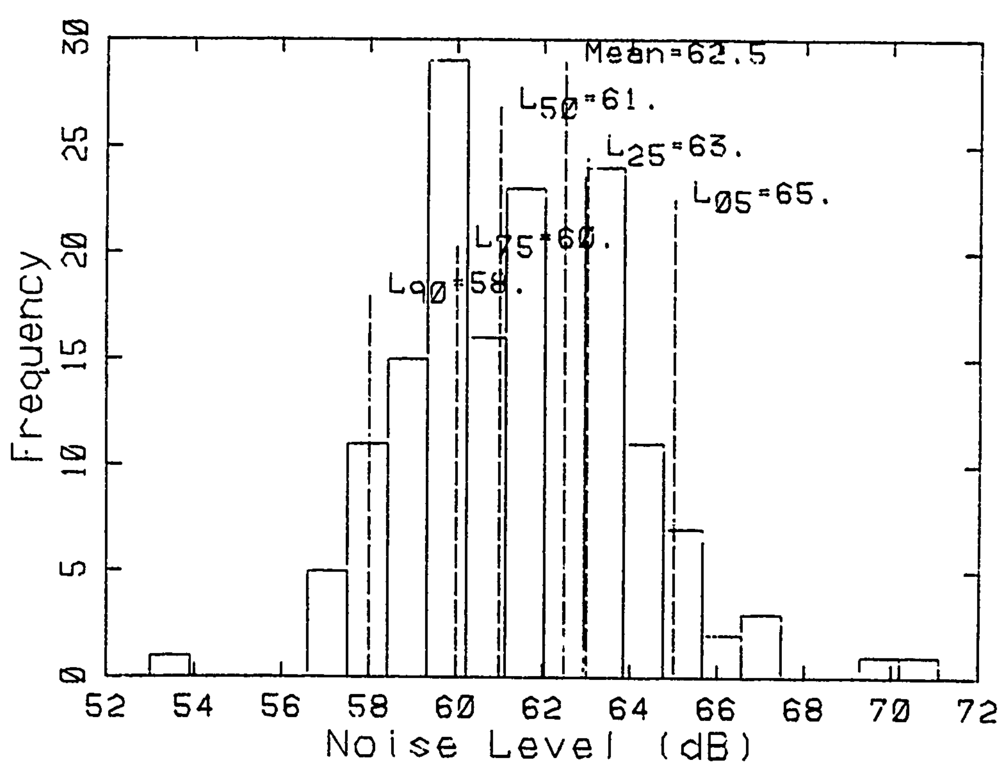

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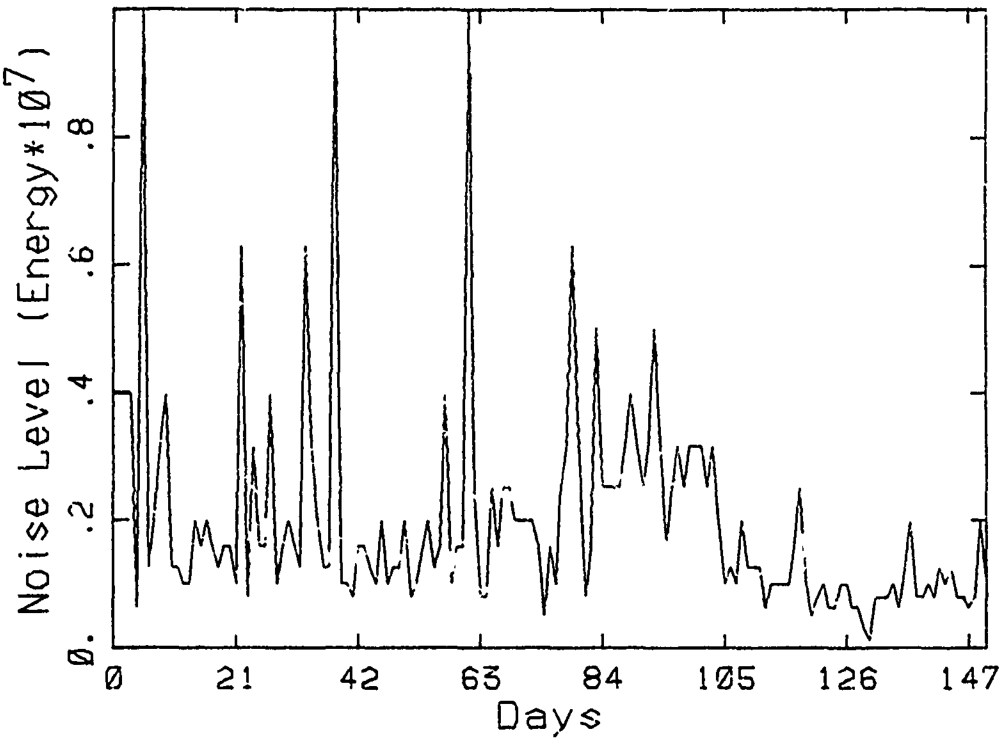

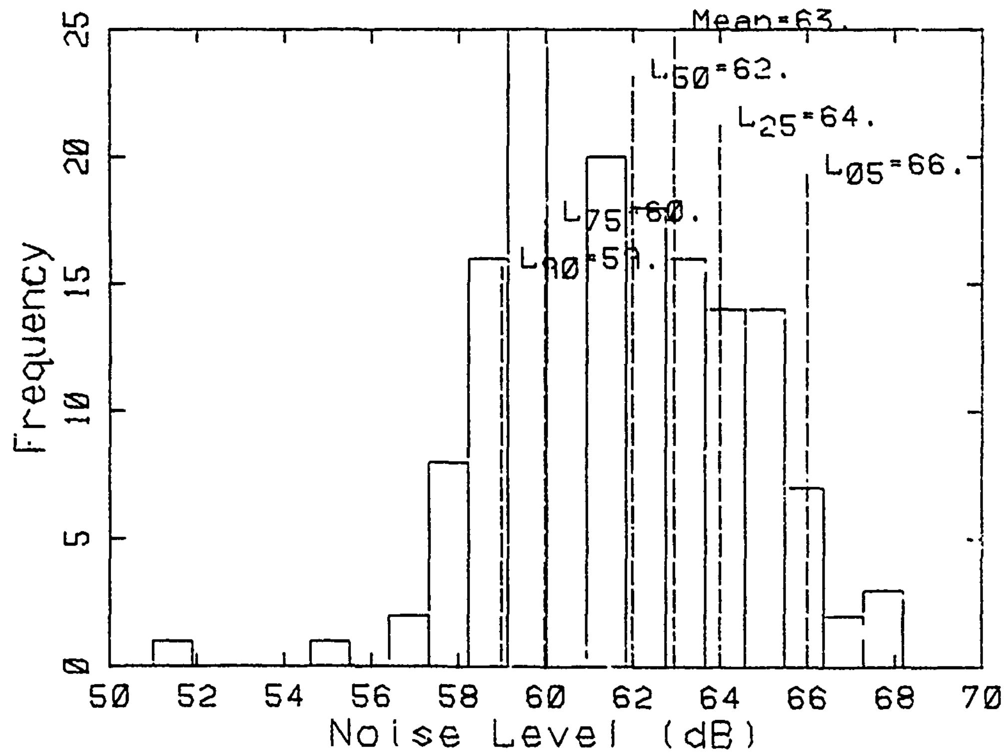

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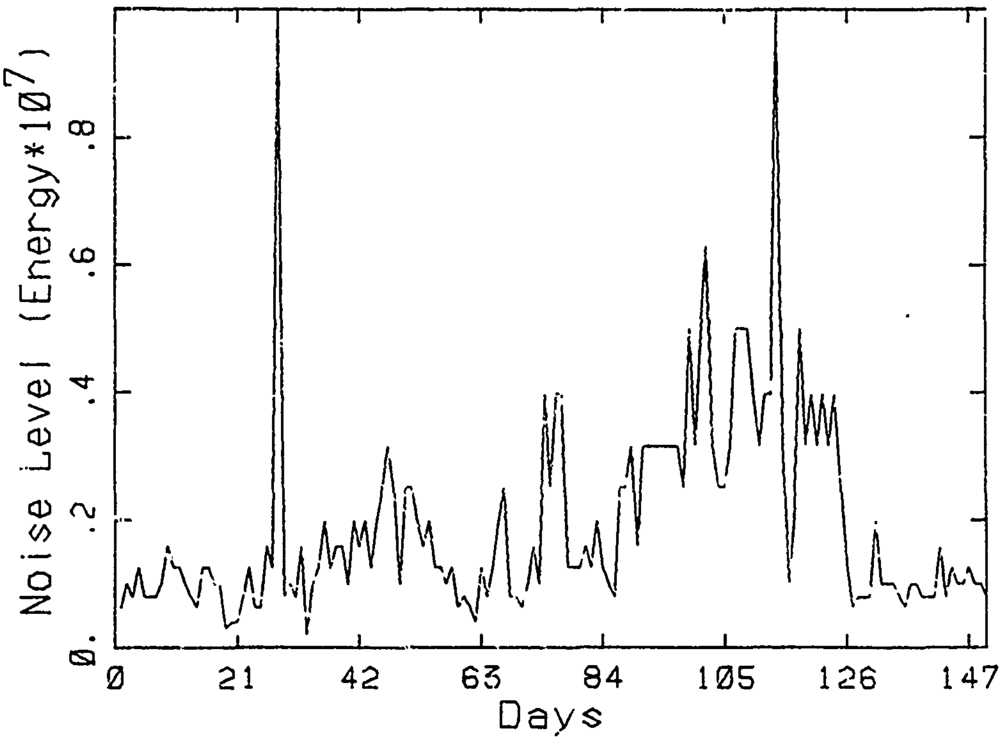

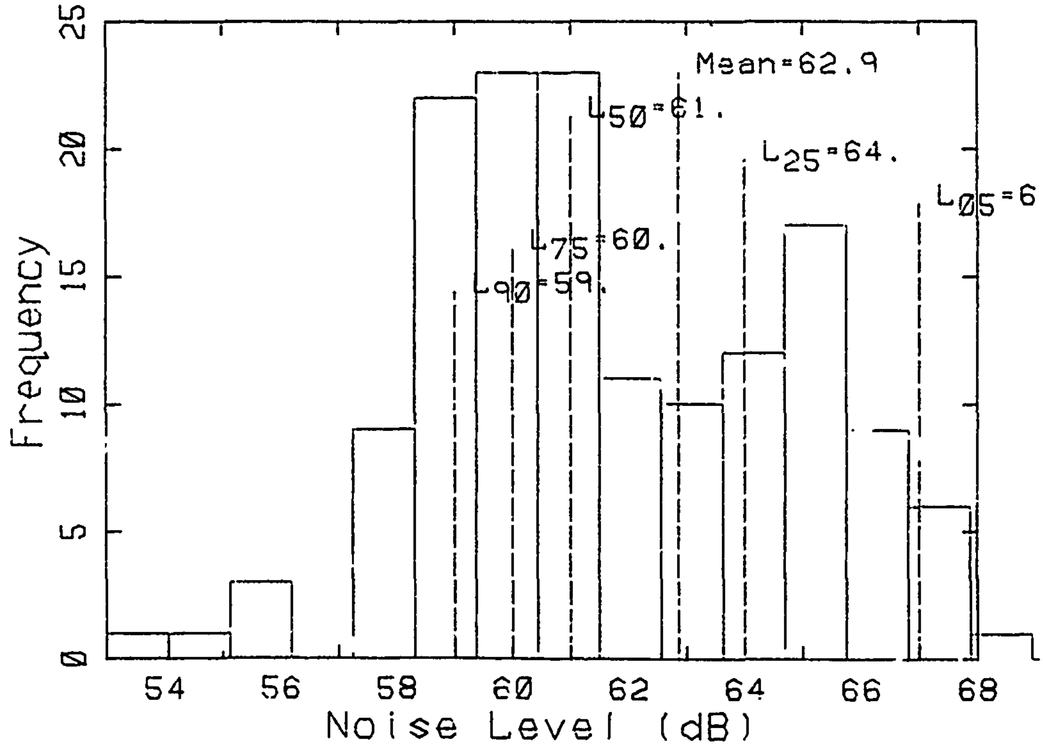

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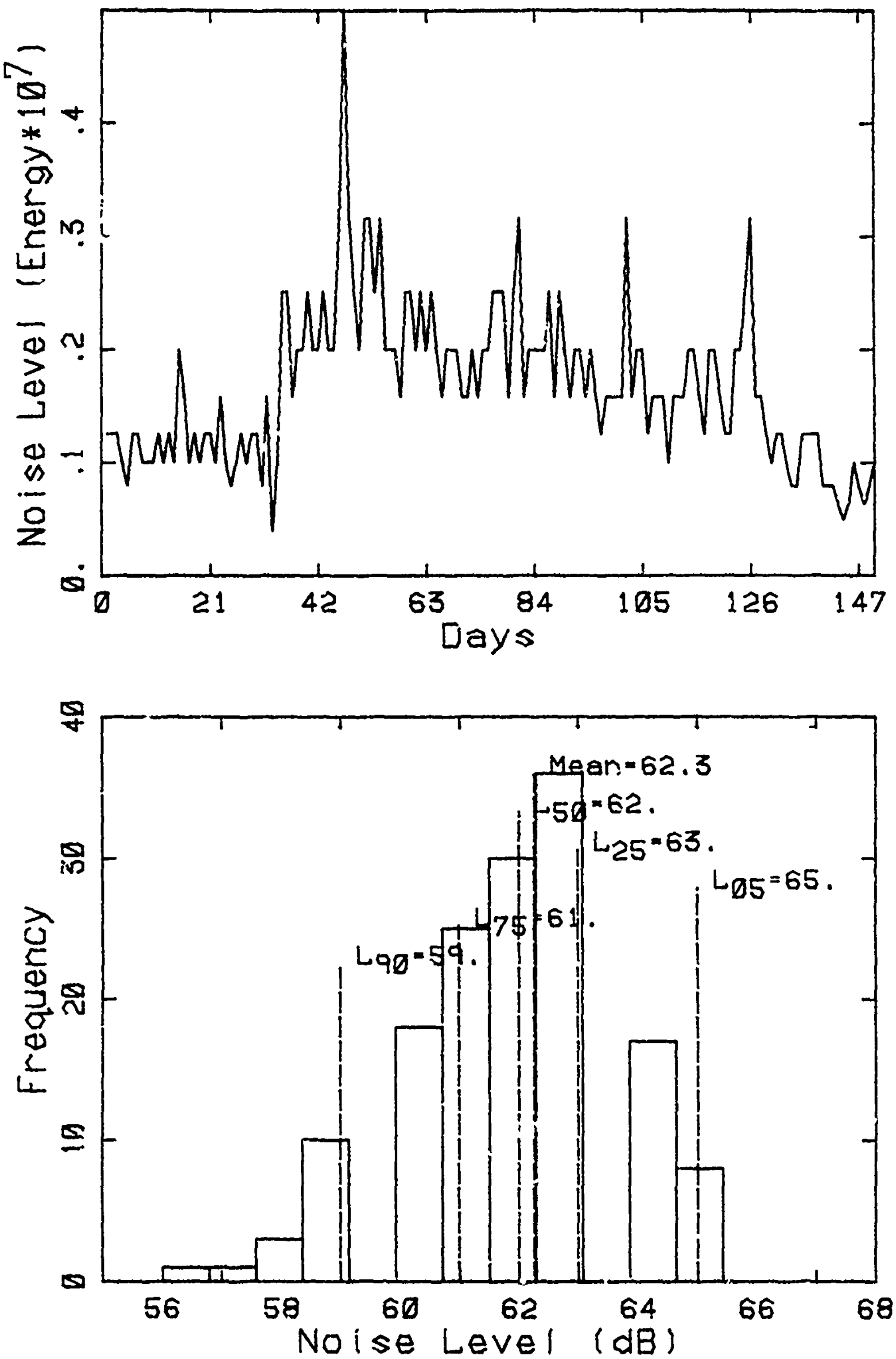

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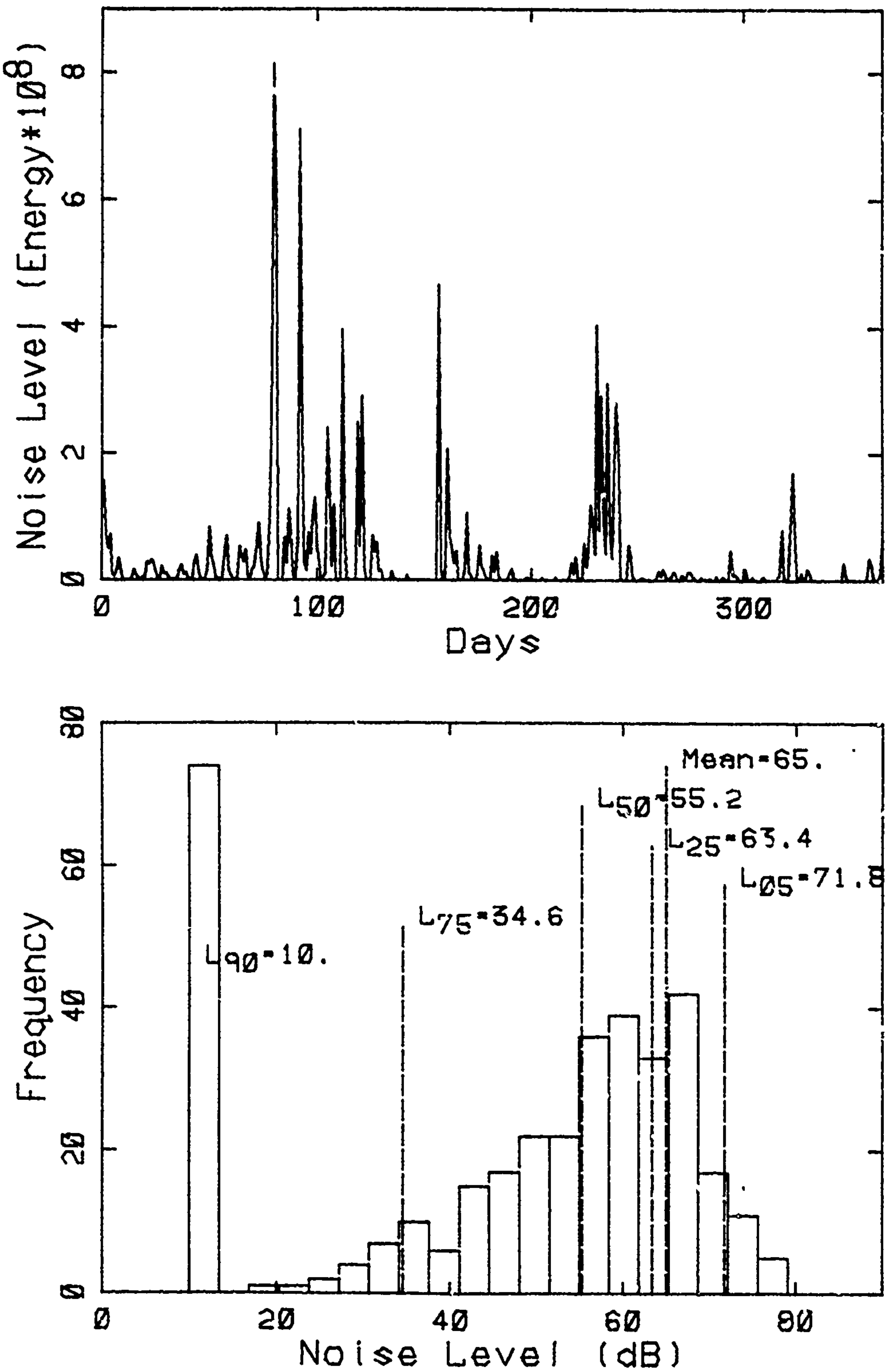
FORT BRAGG MILITARY INSTALLATION HISTOGRAMS AND TIME SERIES PLOTS



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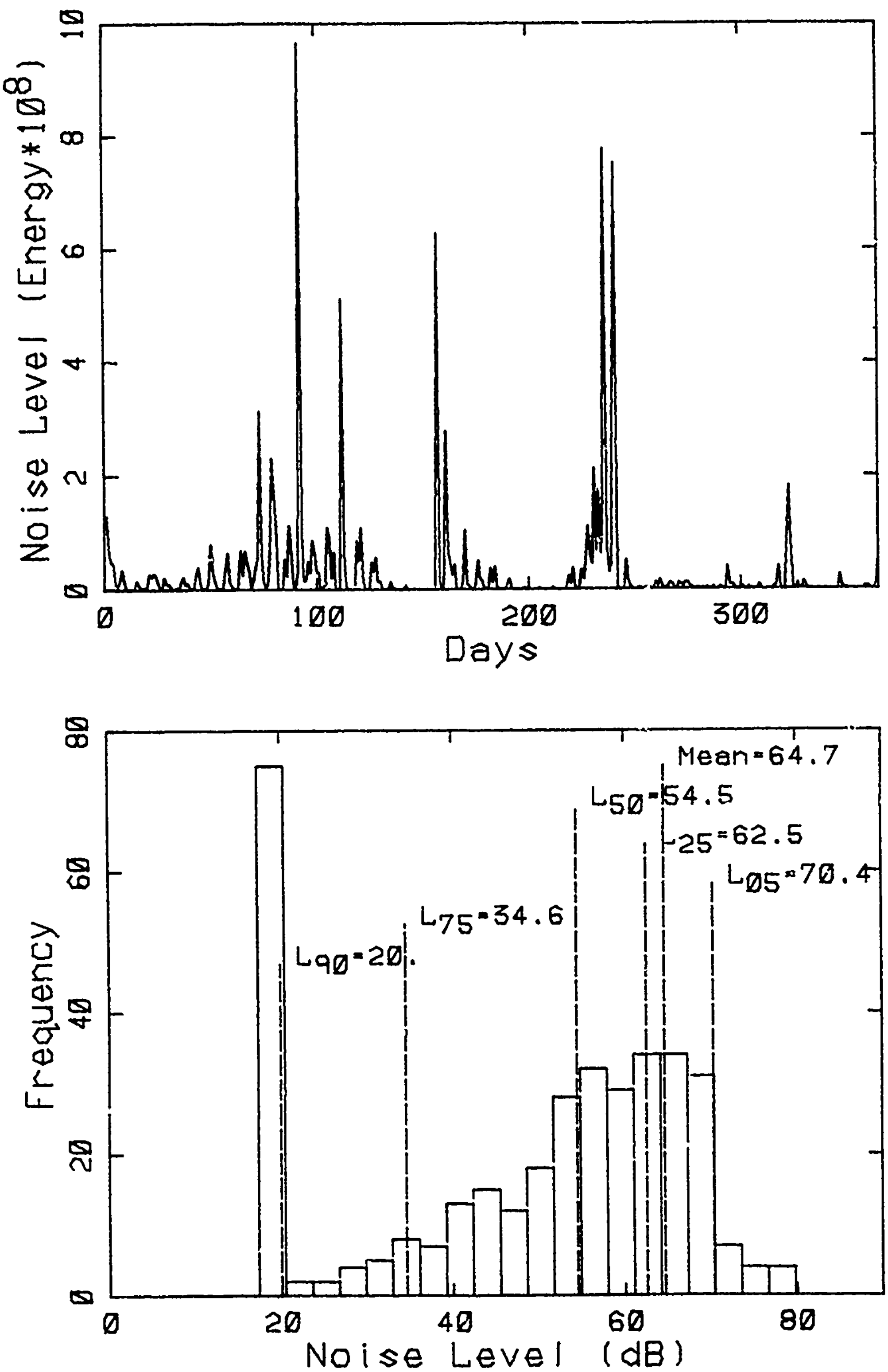

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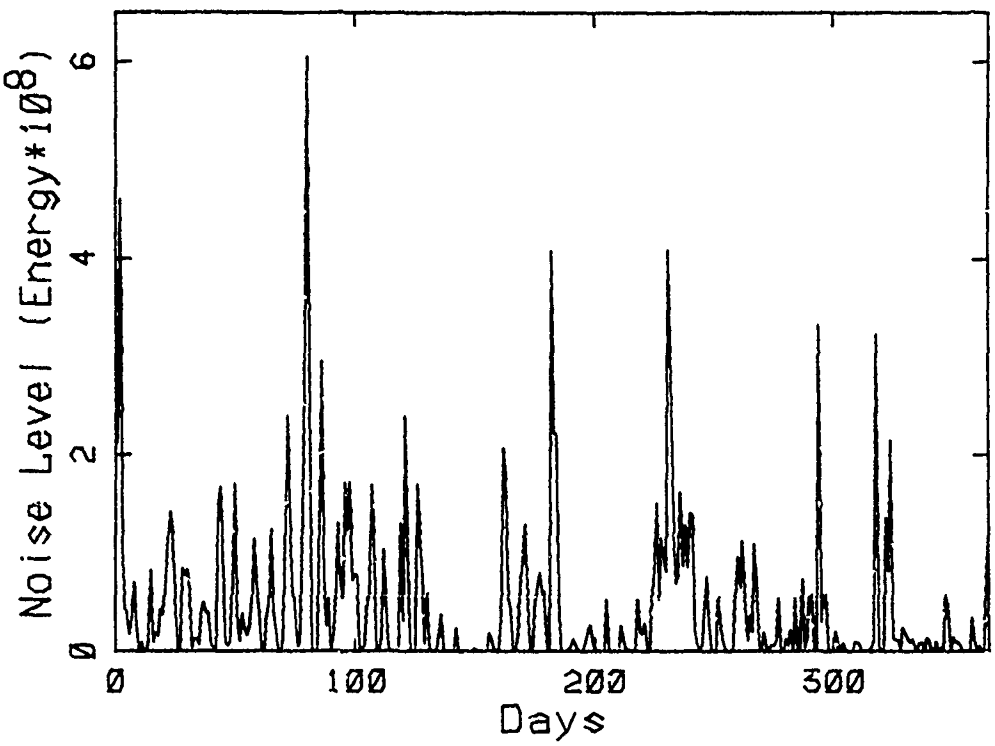

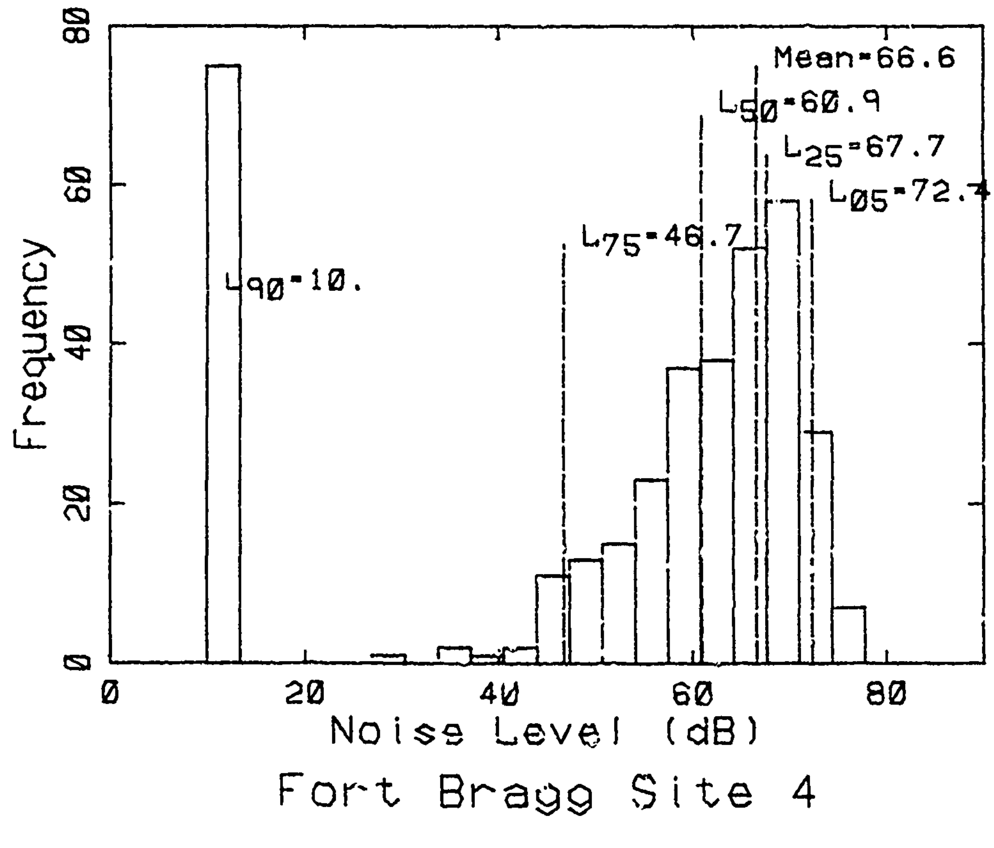

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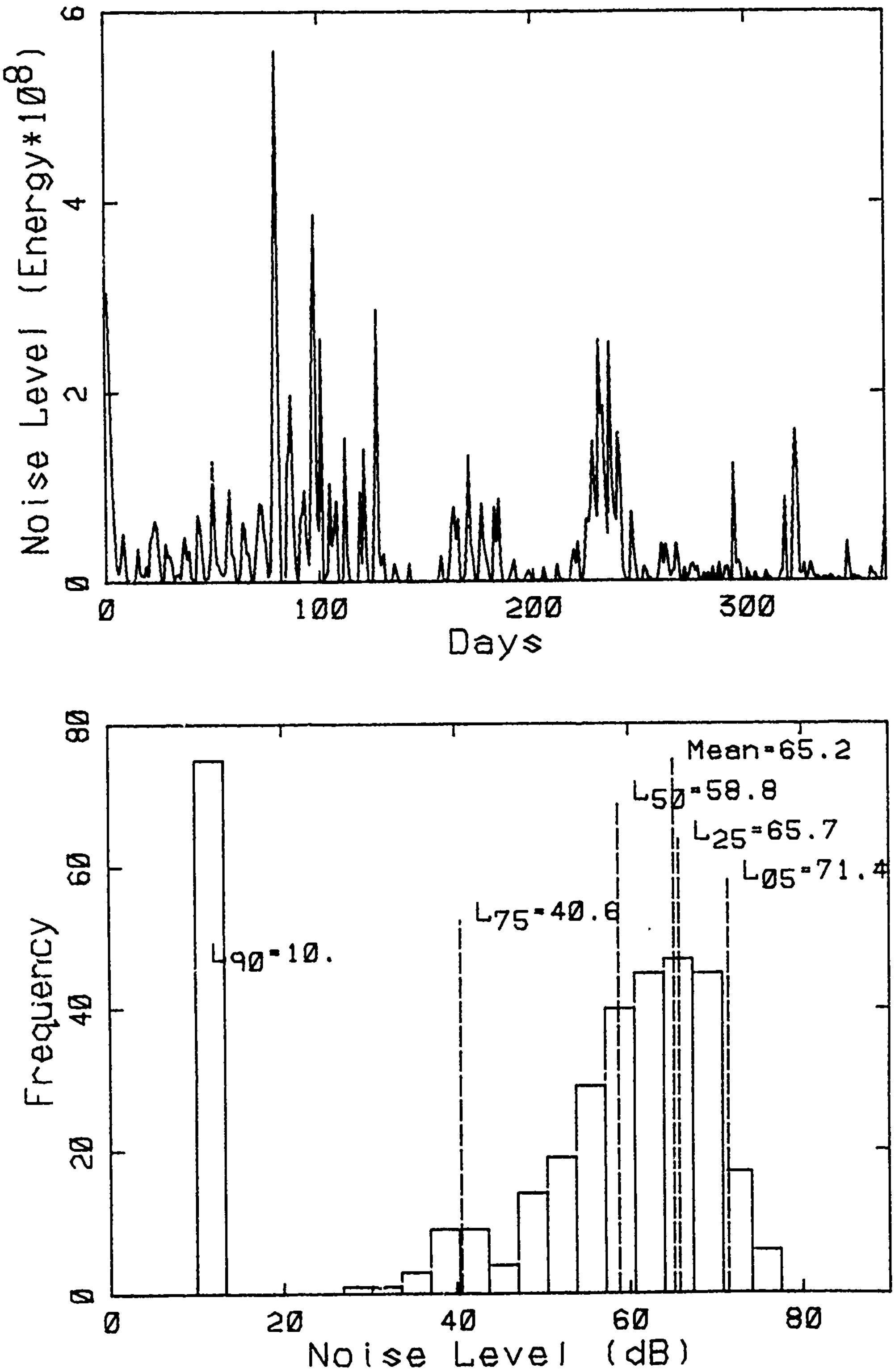

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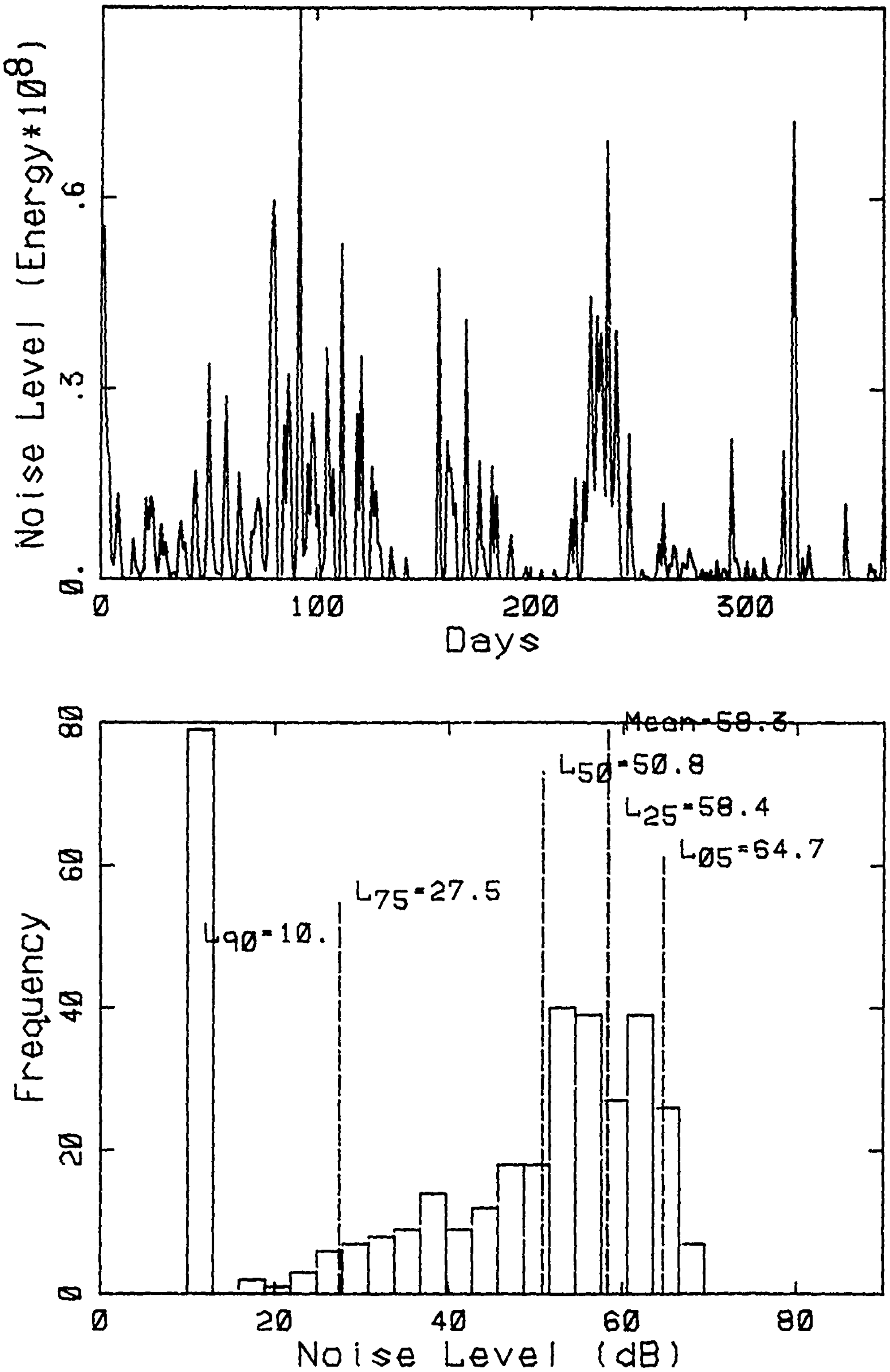

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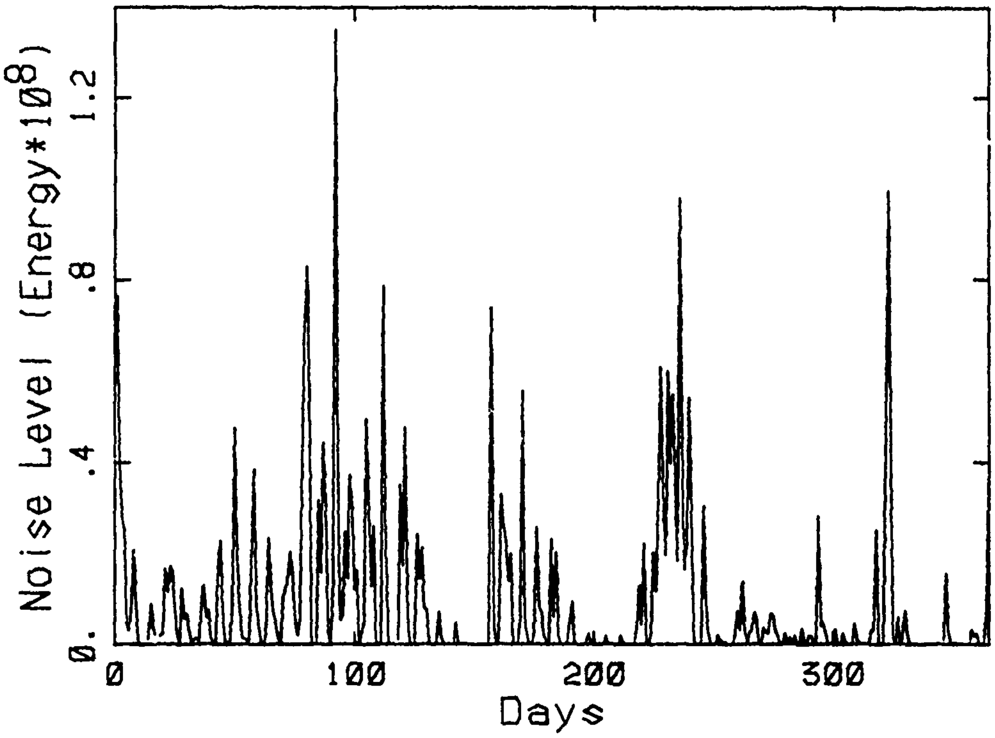

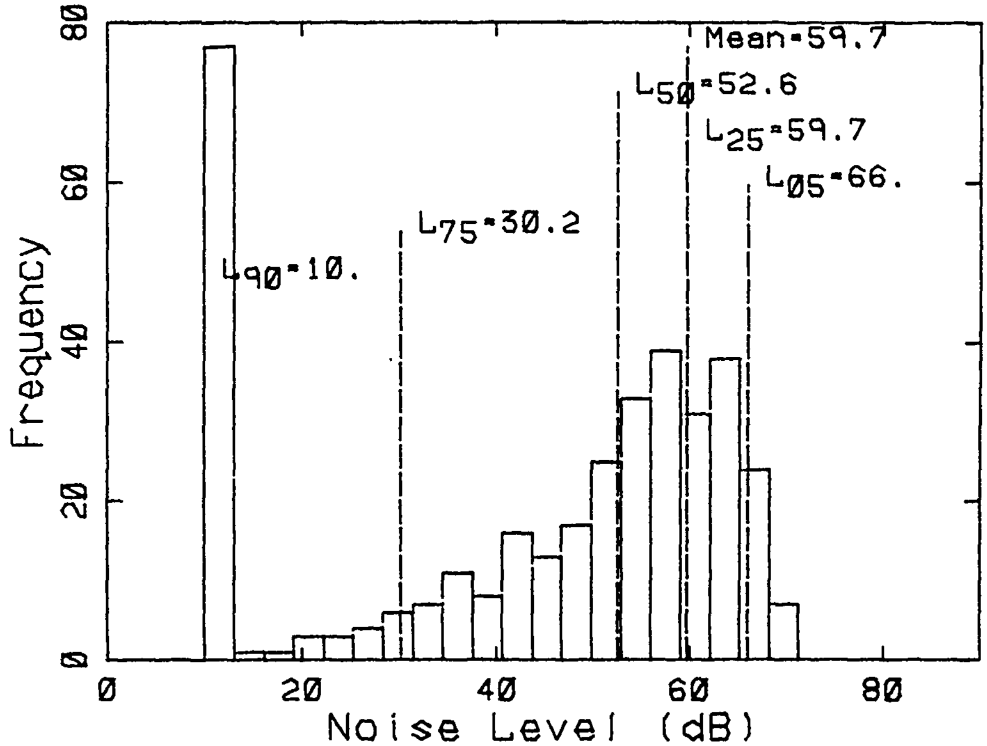

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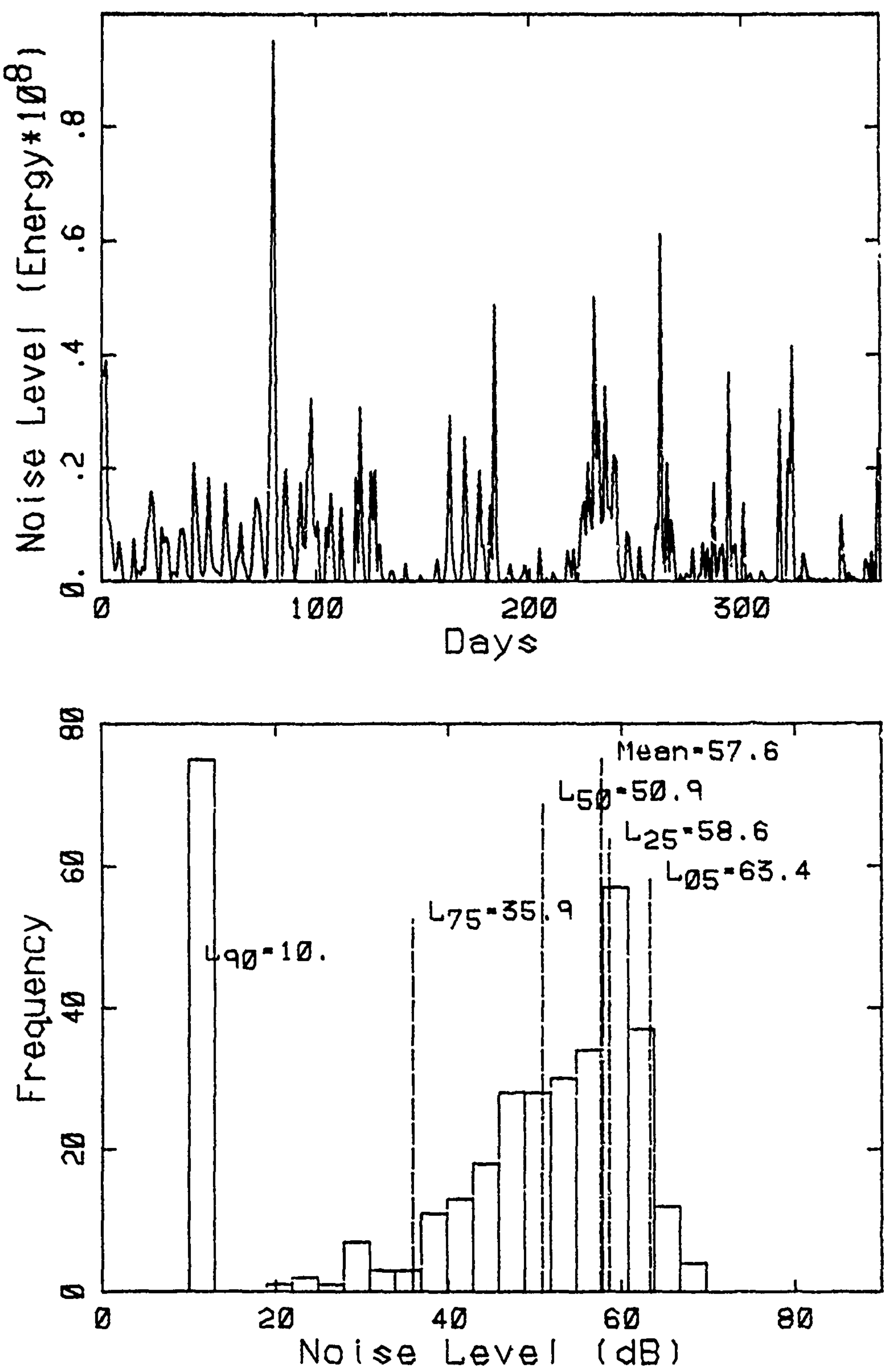

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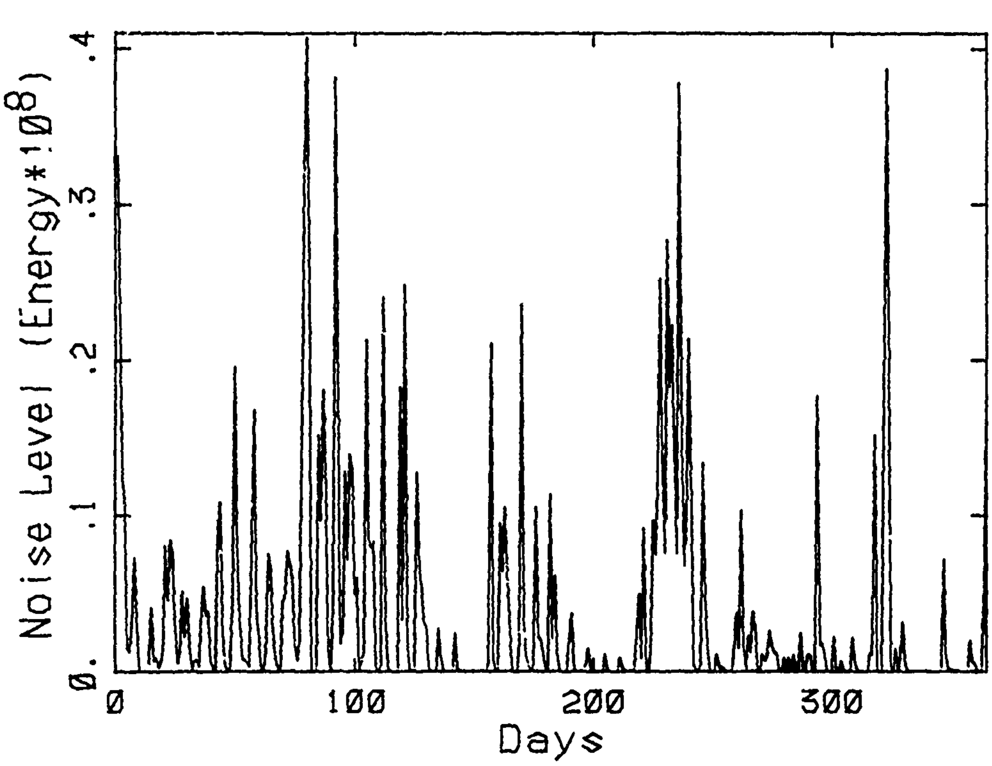

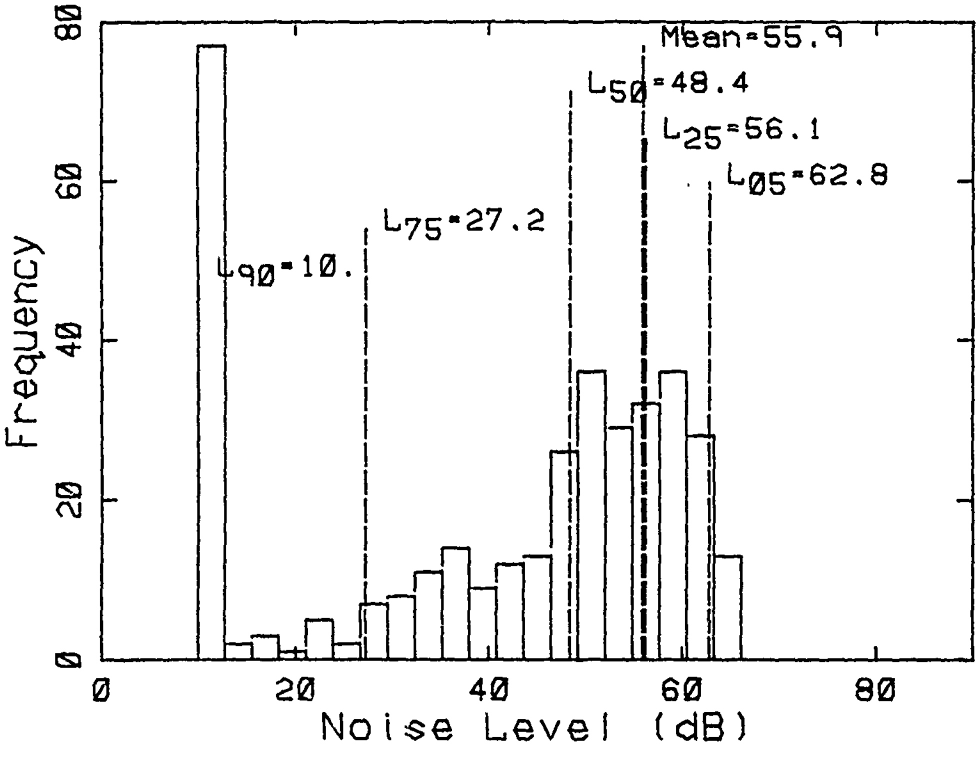

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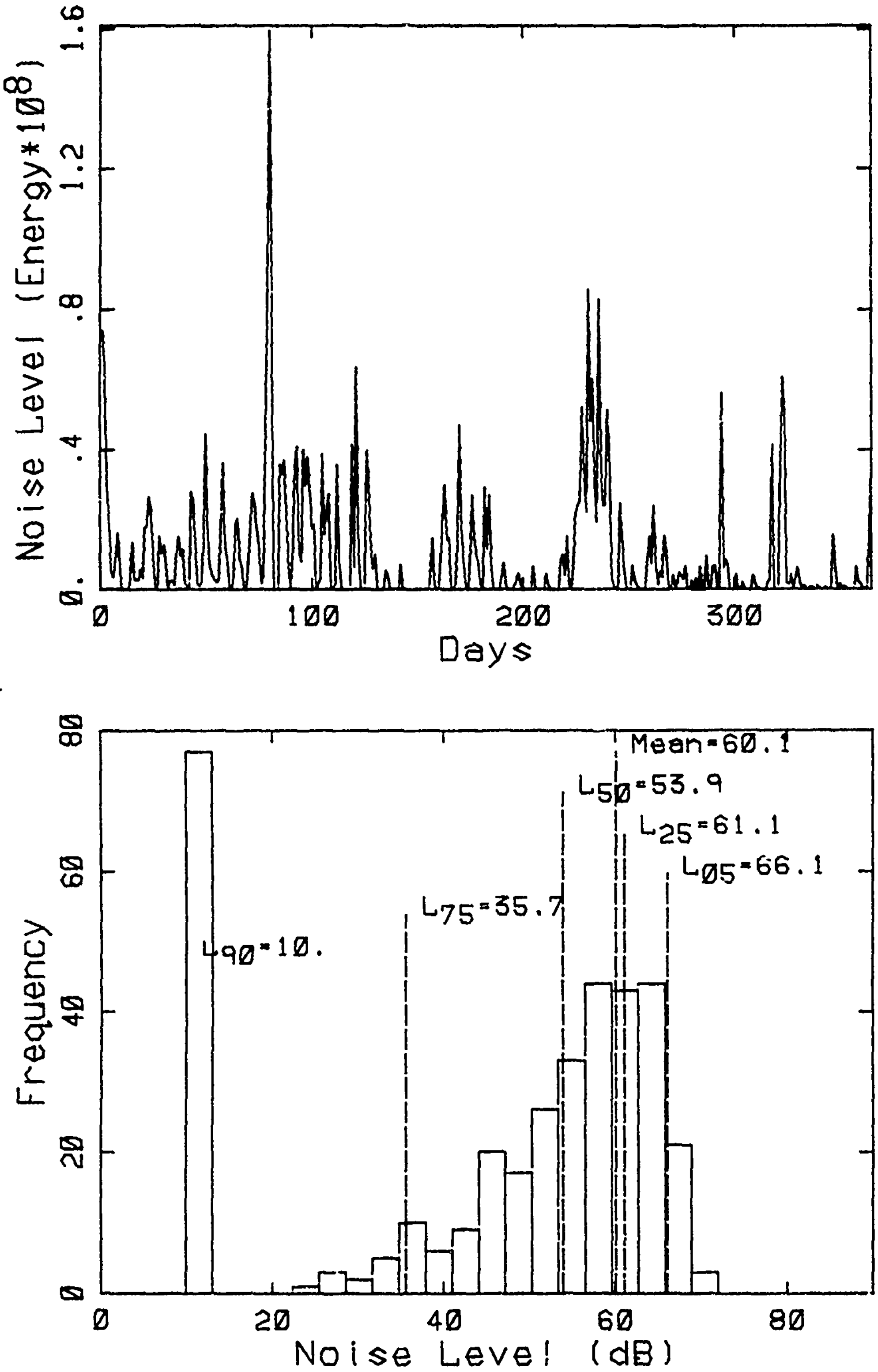

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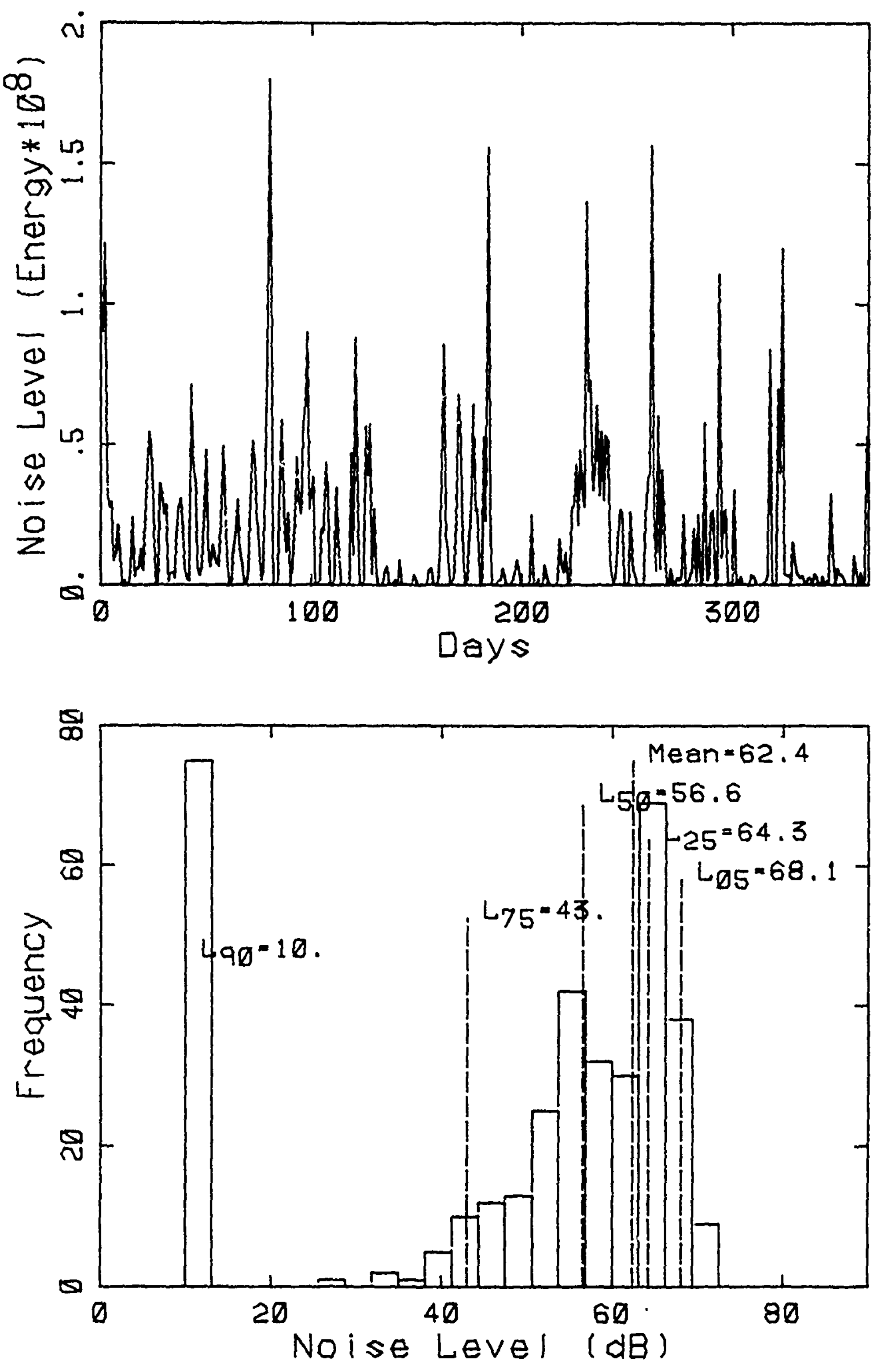

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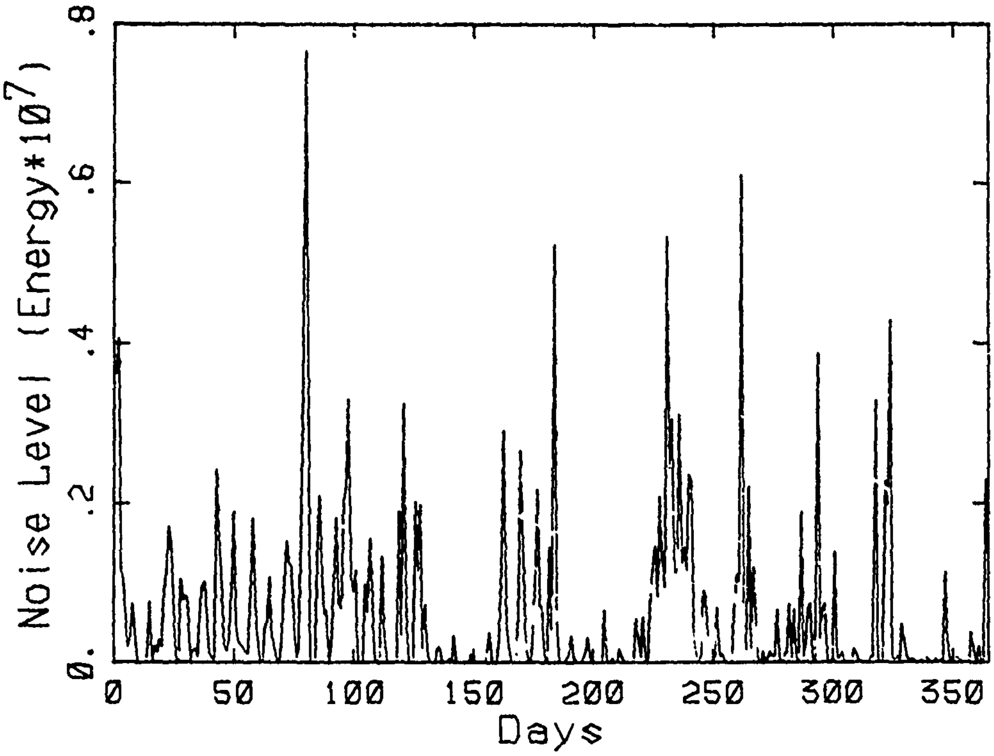

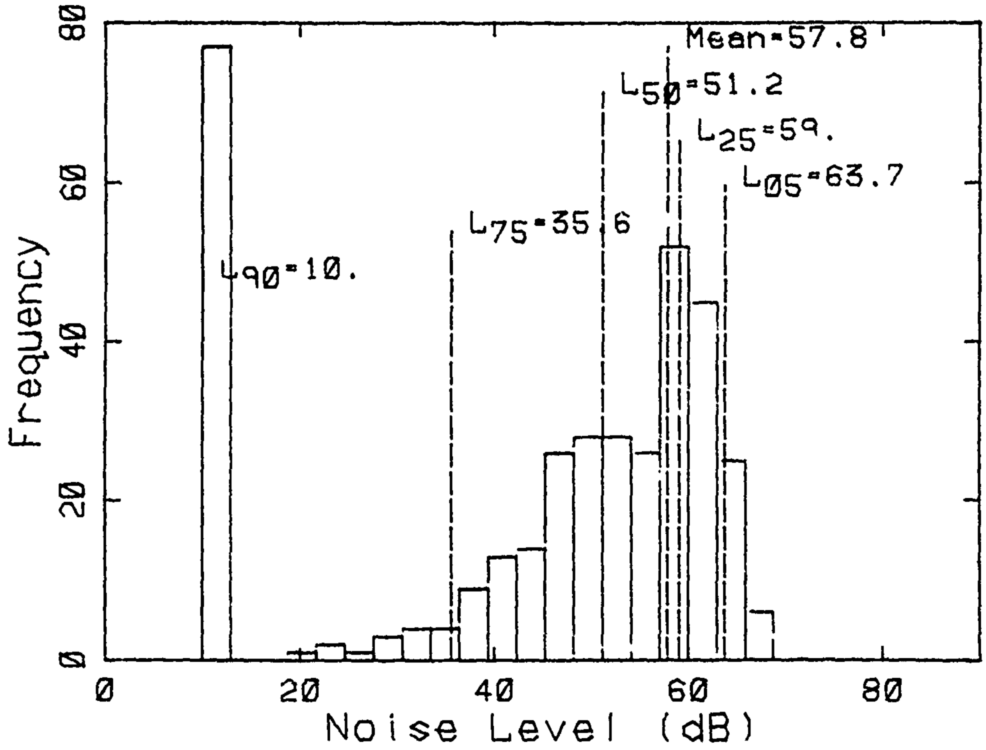

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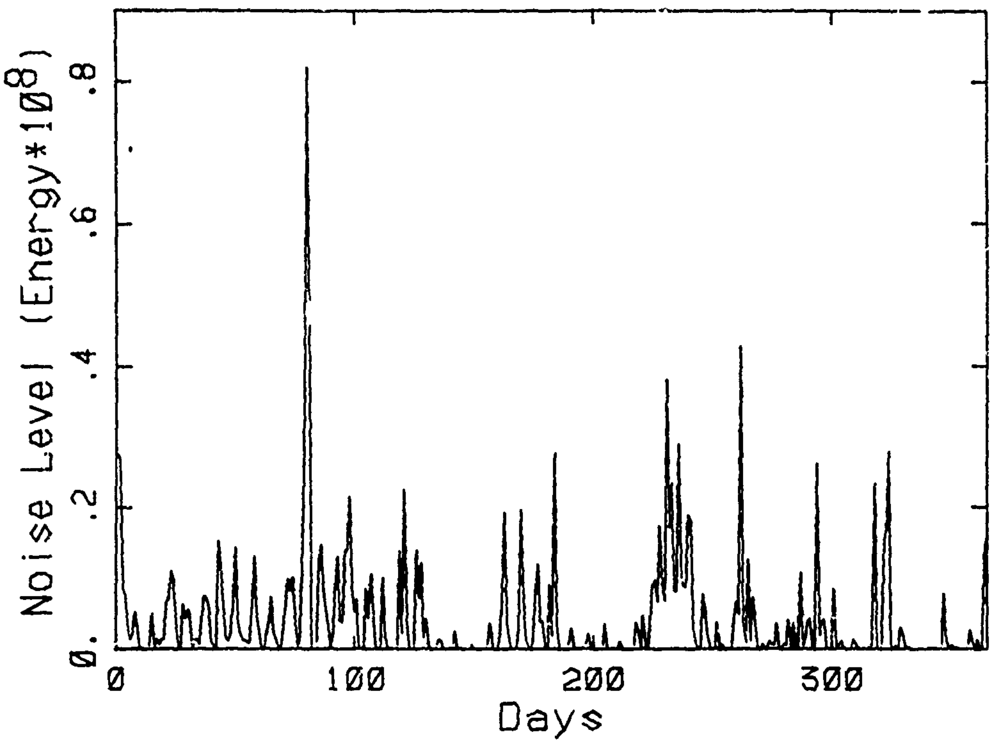

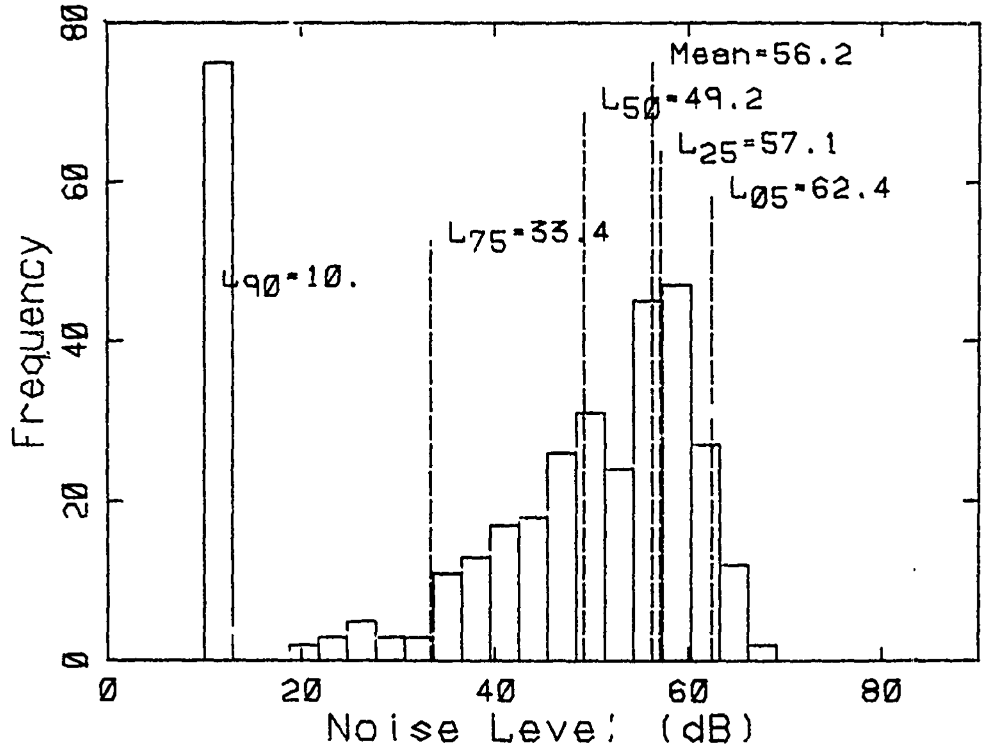

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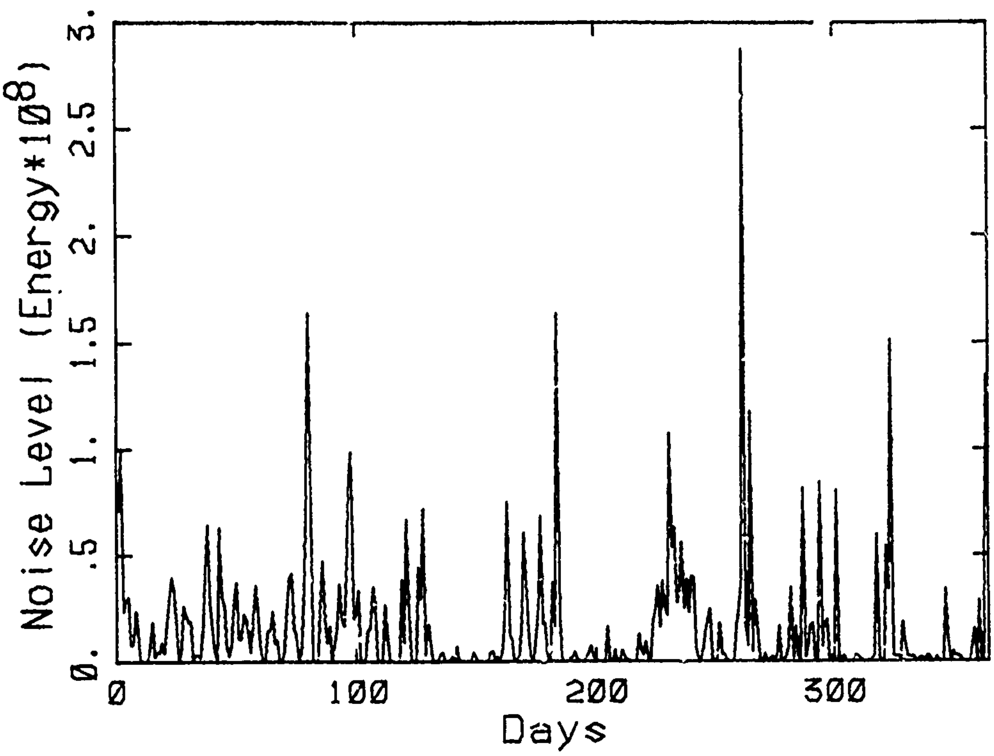

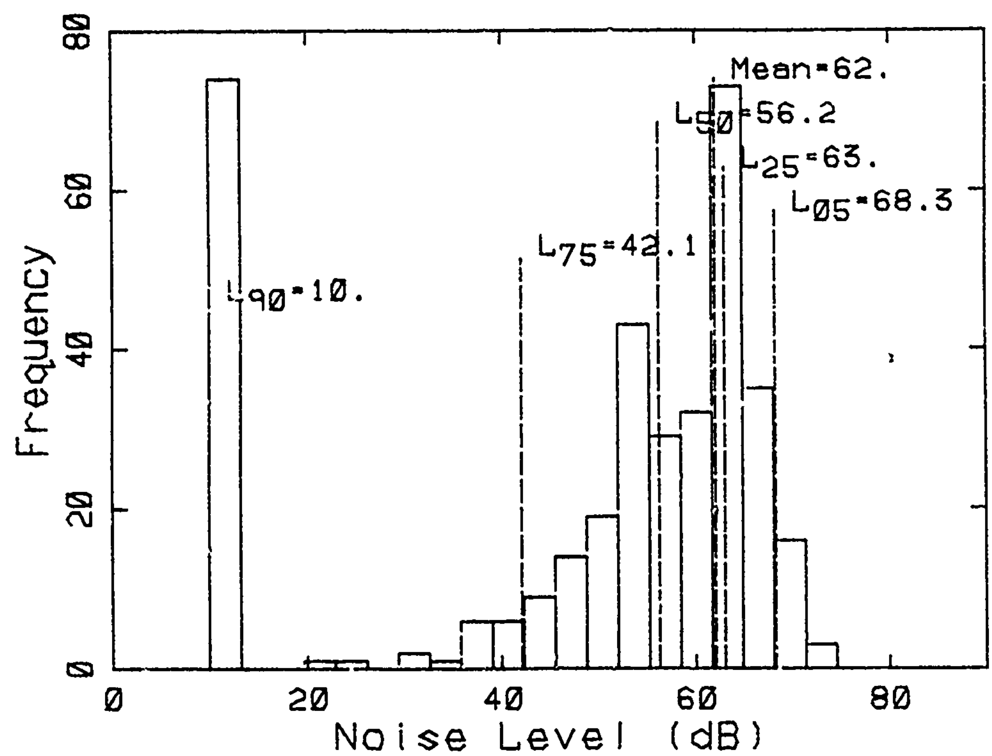

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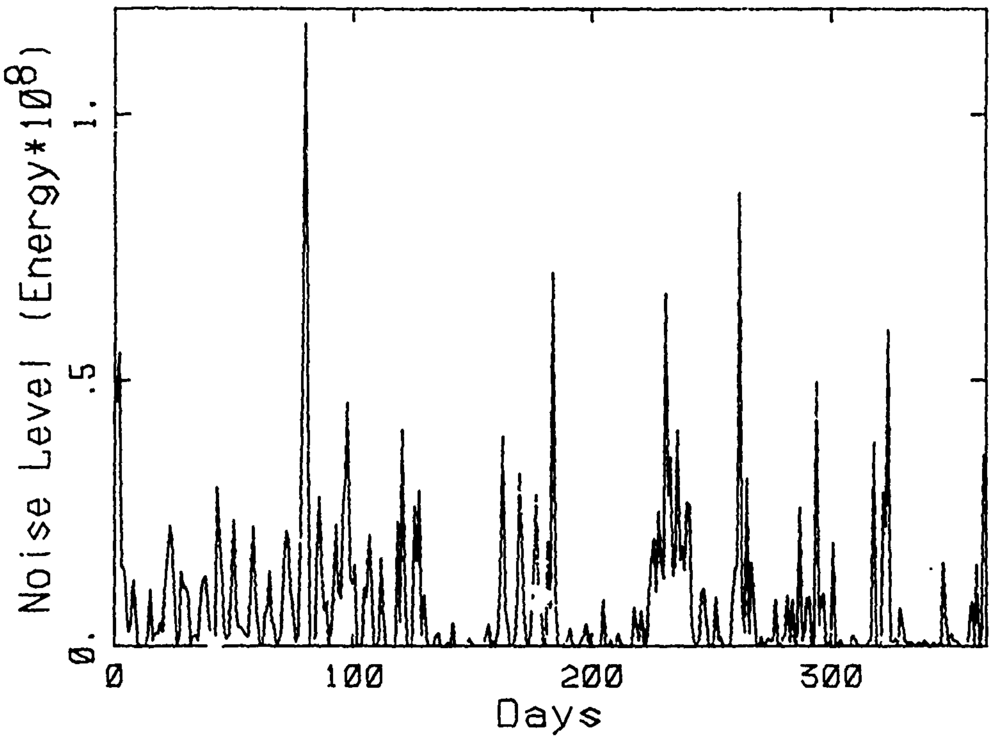

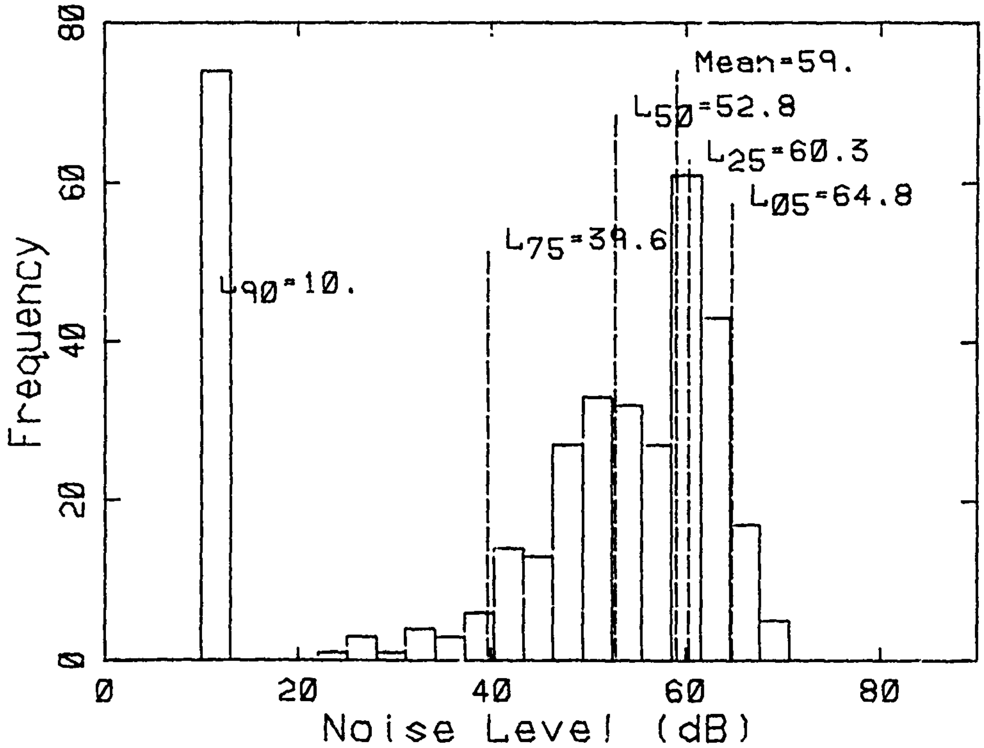

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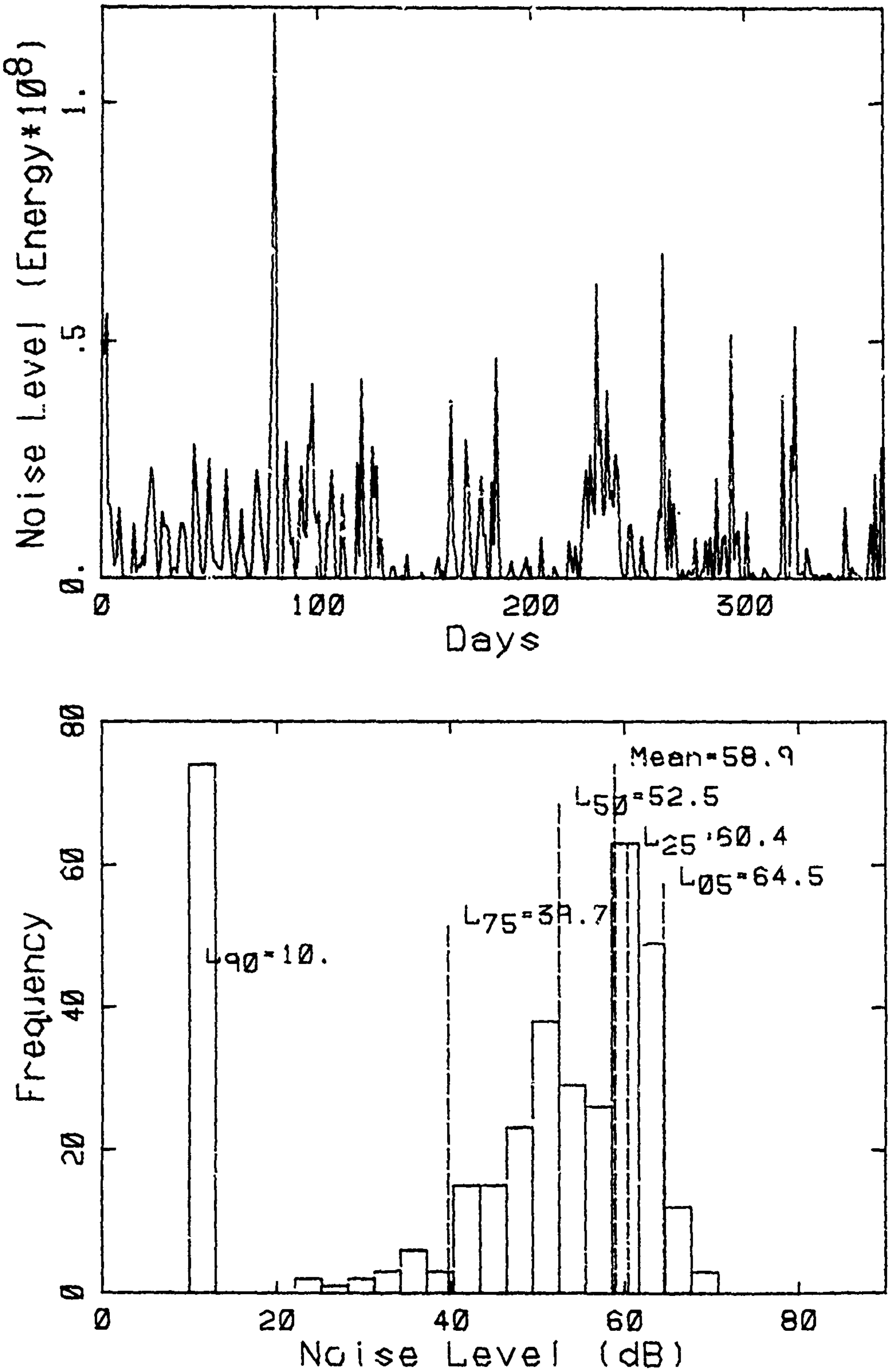

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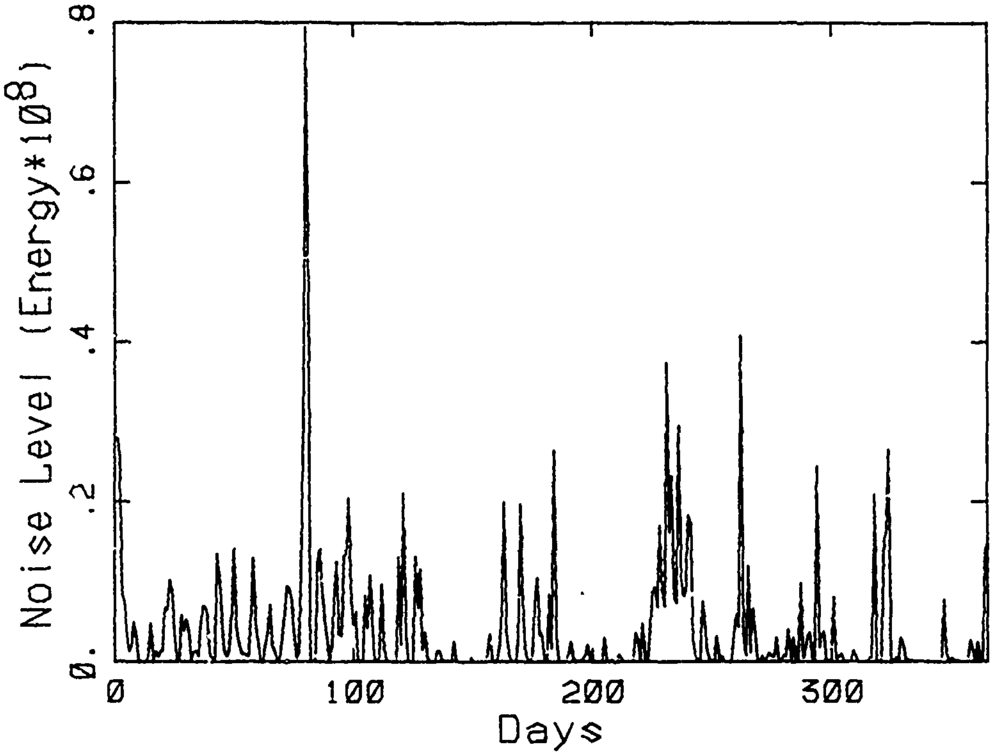

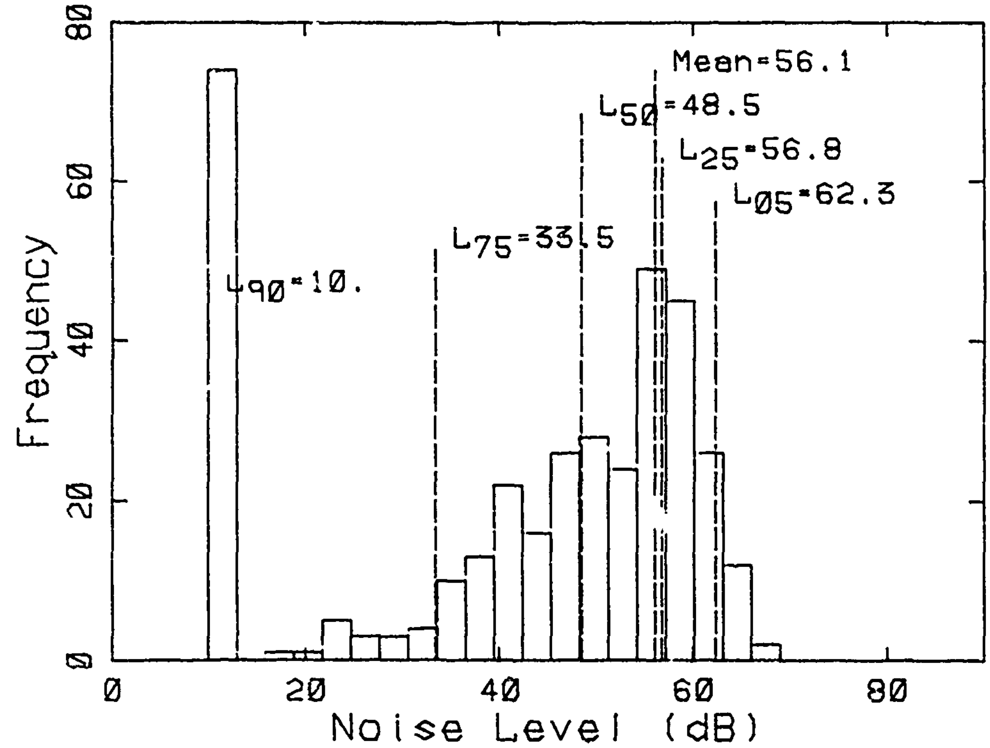

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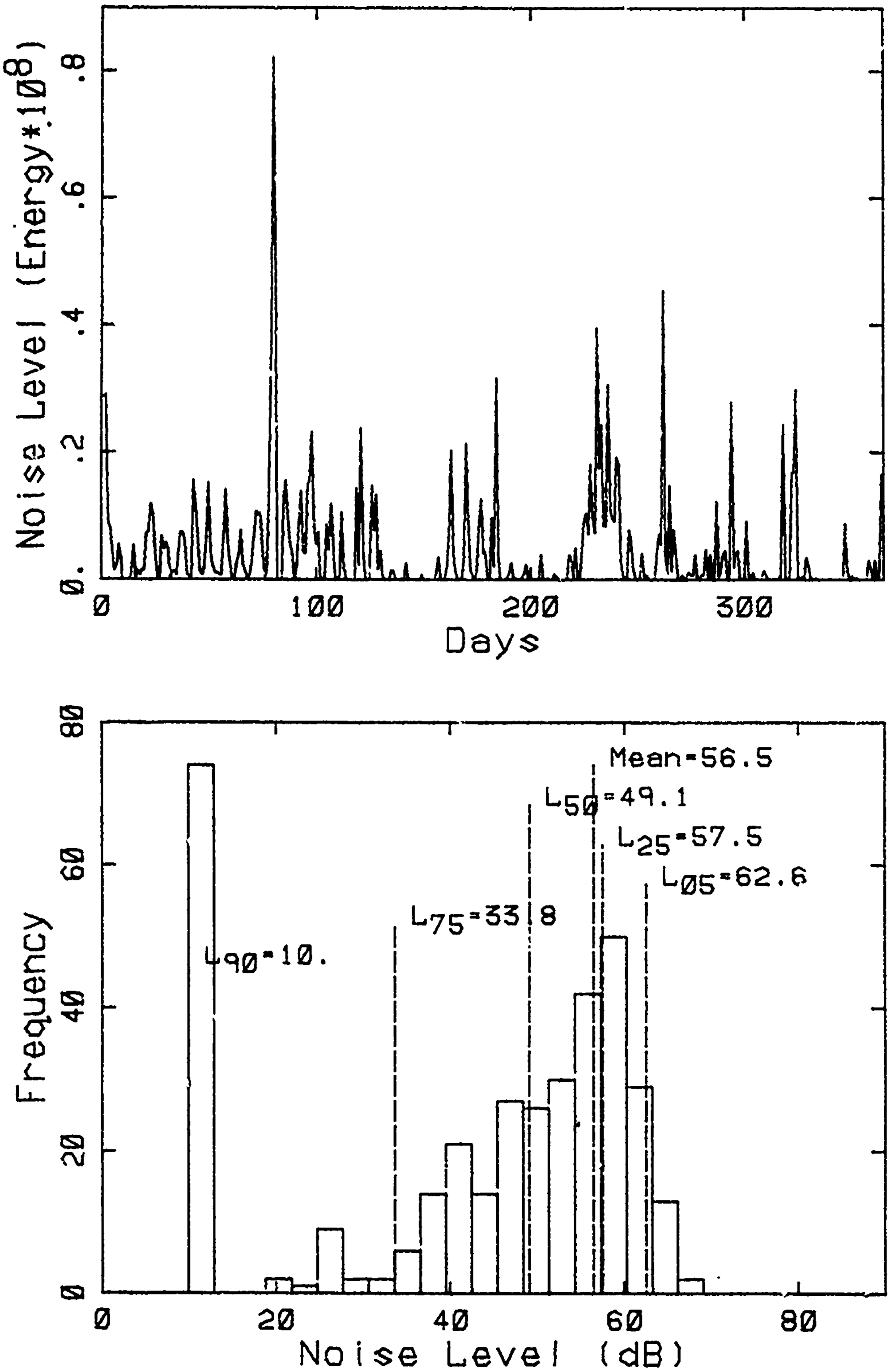

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Temporal sampling requirements for estimating the me.n noise level in the vicinity of military installations / by P. D. Schomer - - - et al. -- Champaign, IL : Construction Engineering Research Laboratory ; Springfield, VA : available from NTIS, 1981.
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